The Reverse Size Effect: Intricate Relationship between Size and Quality in Sweden and the Nordics

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Abstract

We examine the size anomaly in the Nordic countries with a particular focus on its largest individual market, Sweden. First, analyzing return patterns of market value sorted portfolios, we find that large stocks outperform small stocks in Sweden and the Nordics, leading to a *reverse* size effect. Extremes matter as focusing only on the smallest and biggest stocks reveals an enormous negative size premium. In addition, we find a strong seasonality pattern including a substantial January effect. Second, further investigating the recently identified interaction between size and quality, we examine the size effect in the presence of quality factors covering profitability, growth, safety and payout of a firm. We find that the size premium increases, however, it fails to prevail in terms of statistical significance. Moreover, controlling for quality mitigates the seasonality effects but is not able to dismantle the January effect. We find evidence that small stocks feature a high negative exposure to the quality factor and mainly drive the size effect. We discover challenges for asset pricing theory as a comprehensive six-factor model that also controls for size and quality fails to explain returns of small and particularly junk stocks.

Keywords: Size Effect, Size Anomaly, Quality, Junk, January Effect, Sweden, Nordics

JEL classification: G11, G12

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1 Introduction

Since Fama and French (1993) developed their famous three-factor asset pricing model, the small-minus-big (SMB) factor gained far-reaching importance in explaining stock returns. It aims at catching the apparent relative overperformance of small stocks compared to big stocks through a zero cost portfolio that is long small stocks and short big stocks. Size is measured in terms of market capitalization, thus small stocks refer to firms with low market values and big stocks refer to stocks with high market values. The existence of a size premium was first discovered by Banz (1981) in the US market and evolved into one of the most debated asset pricing anomalies. The size effect is scrutinized in academic literature for its low statistical significance, poor historical performance, its variability over time, its concentration among microcap stocks, its strong performance in January but large absence in the other eleven months, the potential of being a proxy for liquidity and its poor performance in markets other than the US.

This study confirms the criticized weak performance of SMB in a sample period from July 1986 to December 2015 and finds a negative and statistically significant size premium of -4.23% p.a. for the Nordic region comprising Sweden, Norway, Denmark and Finland. In the Swedish market, a negative but insignificant size premium of -2.18% p.a. exists that especially developed since the turn of the millennium. In Norway, the small-minus-big strategy yields -0.27% p.a., in Denmark -2.47% p.a. and in Finland -1.92% p.a. Sweden is the largest market in the Nordics in terms of market capitalization and contains approximately half of all Nordic stocks. For this reason, we mainly center our discussion of empirical results around the Swedish economy. However, we also investigate the other Nordic countries Norway, Denmark and Finland individually. Additionally, we analyze the Nordic region as a whole using all stocks of the four individual countries following the results of Annaert et al. (2002) who only find a size premium in the cross-section of the whole European market but not in individual countries. We highlight differences whenever important or surprising, however, findings are generally quite consistent for all countries as well as the combined Nordic sample. Detailed results of these analyses are reported in the robustness section.

Focusing on the Swedish market, we identify a staggering nearly monotonic pattern in returns of decile portfolios sorted on market value. Returns are positively related to size and hence increase with market capitalization. Interestingly, the pattern is stronger since the turn of the millennium. Given the nearly monotonic relation between size and returns, the most extreme size decile portfolios show an even stronger size effect. The $P1 - P10$ decile spread yields -35.46% annually over the sample period. Therefore, we show that the Swedish market is characterized by a *reverse* size effect.

Very recently, however, Asness et al. (2015) find that all common criticisms of the size effect are dismantled in the US market after controlling for a quality-minus-junk (QMJ) factor leading to the conclusion that QMJ resurrects the size effect. Quality refers to a composite measure of a set of characteristics that capture profitability, growth, safety and shareholder friendliness of a firm. This definition is based on the dimensions of the Gordon growth model and follows Asness et al. (2014). Research in international markets has not yet focused on this topic and no study has been conducted that particularly investigates the size effect and its interaction with quality in the Swedish market or the Nordic region in general. The purpose of this study is to close this gap and to examine the size anomaly in Sweden and the Nordic countries with a particular focus on the quality dimension introduced by Asness et al. (2014).

We untangle the interaction between size and quality and find that the two characteristics are linked as Asness et al. (2015) have already pointed out. We show that small stocks feature poor returns and tend to be of rather low quality (referred to as junk) compared to stocks with high market values. Stunningly, the average quality monotonically increases with size in decile portfolios sorted on market values. Reversing the analysis and constructing decile portfolios sorted on quality scores reveals that especially returns of the lowest quality or junk stocks are fairly weak. Building a set of 25 portfolios independently sorted on size and quality, we show that only substantial negative returns of smaller and lower quality stocks are statistically significant. In line with recent academic literature, this challenges proposed risk-based explanation of returns, which would require small and junky stocks to earn a premium in compensation for their risk. We conclude that the *reverse* size effect is primarily driven by these small junk stocks.

Furthermore, we show that controlling for quality partially restores the SMB premium by lifting it into positive territory for the individual Nordic countries Sweden, Norway, Denmark and Finland. The size premium also increases considerably for the whole Nordic region, however, it stays insignificantly negative. Thus, we confirm the impact of controlling for exposure to quality/junk, though not to the same extent as shown by Asness et al. (2015) in the US market as statistical significance remains to be an issue for full sample SMB premia.

A further characteristic of the Nordic markets, and the Swedish market in particular, is a strong January effect. While average returns of SMB are economically significant and positive in January, cumulative returns in the remaining months are negative leading to the aforementioned negative yearly SMB premium. Again, we show that extremes matter as the $P1 - P10$ decile spread of portfolios sorted on market capitalization yields even higher returns in January, but lower returns in the remaining months of the year in comparison to the classical SMB factor portfolio that utilizes the whole universe of stocks in its construction. According to Asness et al. (2015), the size premium emerges in every month after controlling for quality and thus eliminating the behavior of small junk stocks that dilute the size effect at certain times. Indeed, after controlling for quality, SMB returns in the Swedish market are not significantly different from each other in January and the non-January months in the first subset of our full sample period from July 1986 to December 1999. Interestingly, we find significant and substantial January returns in the period from January 2000 to December 2015, which are the only source of statistically significant positive SMB returns after controlling for quality. Moreover, consistent with Asness et al. (2015), we show that common liquidity measures do not explain the size effect in the Swedish market after controlling for quality.

Lastly, we test the explanatory power of current asset pricing models on the intersection of size and quality in order to uncover which sets of stocks provide significant abnormal returns. Therefore, we individually investigate six portfolios independently sorted on size and quality, which are used to construct the QMJ factor. We discover that junk stocks show significant alphas that cannot be explained through a six factor model including the market factor MKT, its lagged value, the size factor SMB, the value factor HML, the momentum factor MOM and the quality factor QMJ. This result is puzzling as controlling for size and quality should have eliminated all exposure to these factors, but apparently, junk stocks contain returns that are not subsumed. Even more interestingly, small junk stocks earn a negative alpha and big junk stocks earn a positive alpha. In Sweden these amount to -70 bps per month and 74 bps per month, respectively. Therefore, we show that the behavior of junk stocks in general and not just small junk stocks provides a challenge to asset pricing theory. In fact, it is the junkiest set of stocks that are the least explained by current asset pricing models.

The paper proceeds as follows. Section 2 provides a brief overview of relevant literature regarding the size premium in the US market and in international markets. Besides, challenges, anomalies and explanations of the size effect are introduced. Section 3 characterizes our dataset and focuses on different methods of portfolio construction. The methodology used in this paper is presented and each factor is described in detail. Subsequently, we report our empirical results in Section 4. In Section 5, we test the robustness of our results before we summarize and conclude our findings in Section 6, highlighting open questions for further research.

2 Related Literature

Since Banz (1981) and Reinganum (1981) discovered the so-called *size effect* many studies have been conducted to investigate the apparent overperformance of small stocks compared to big stocks. Though a great number of researchers find evidence in support of the existence of a size premium, different papers show vastly varying results depending on the analyzed time period, geographies, sorting methods and portfolio construction mechanisms in general. Moreover, believers in the size premium face a great opposition in academic literature and several major challenges for the size effect have been identified. Common criticisms include an overperformance in January compared to a large absence of the size premium in the other eleven months, a concentration of the size effect among microcap stocks, a generally low significance of returns related to size, the disappearance of the size effect in the 1980s and 1990s, the potential of being a proxy for a liquidity effect as well as a weak performance outside of the US market.

Generally, two main sets of explanations for the anomalies of the size effect prevail. While many researchers support risk-based theories, a different set of explanations is based on behavioral biases such as over-confidence, over-optimism and investors' preference. In the following we provide a brief overview of relevant literature regarding the size effect.

2.1 Empirical Evidence

2.1.1 US Market

Banz (1981) is credited with the discovery of the size effect. Investigating all common stocks quoted on the New York Stock Exchange (NYSE) from 1936 to 1975, he finds that smaller firms with respect to market value have had higher risk adjusted returns, on average, than larger firms. Hence, he uses market value as a proxy for firm size. Moreover, he finds that the size effect is not linear in market value. Returns of very small firms are relatively high and in comparison returns of averaged size and large firms are not that different to each other. This leads to the conclusion that the size effect is concentrated among microcap stocks.

Subsequently, Brown et al. (1983) examine 566 stocks from the NYSE and American Stock Exchange (AMEX) and find an approximately linear relationship between average daily returns on 10 equally-weighted size-based portfolios and the logarithm of the average market capitalization. However, they also show that the methodologies used have an influence on the conclusion about the size effect. Keim (1983) extends the dataset by including all listed firms on the NYSE and AMEX from 1963-1979 and reports a strong size effect, which is mainly due to January abnormal returns. This anomaly is known as the *January effect*. Instead of looking at exchange-traded securities, Lamoureux and Sanger (1989) look at stocks that were traded in the OTC market and quoted on the NASDAQ system from 1973-1985. They also find strong size and January effects confirming earlier studies that are based on different datasets.

Even though a significant and big size premium is identified in different studies using data until the 1980s, the effect seemed to have weakened and disappeared in the 1980s and 1990s after its discovery. Dichev (1998) and Amihud (2002) find evidence that small firms do not outperform big firms during the 1980s and 1990s. Accordingly, Horowitz et al. (2000a) find no consistent relationship between size and realized returns using three different methodologies including annual compounded returns, monthly cross-sectional regressions, and linear spline regressions. Analyzing all NYSE, AMEX, and NASDAQ operating firms from 1979-1995, all three methods fail to establish an enduring pattern between size and realized returns. Chan et al. (2000) identify a change from historical relationships as well. From 1984-1998, the annual return on the Russel 1000 Index of large-cap stocks outperformed the Russel 2000 Index of small-cap stocks by 6.49% making the size effect obsolete. According to Schwert (2003) the disappearance of the size effect might be caused by its very discovery coinciding with the formation of various small-cap indices and funds. Dimensional Fund Advisers with Eugene Fama as its Director of Research only serves as one prominent example.

Most recently, Asness et al. (2015) control for quality or junk of a firm and find a strong and robust size effect, that is stable through time including the 1980s and 1990s, robust to specification, more consistent across seasons and markets, not concentrated in microcaps, robust to non-price based measures of size such as sales, number of employees and book equity, and not captured by an illiquidity premium. Using the quality-minus-junk (QMJ) factor proposed by Asness et al. (2014) as a way to control for quality, Asness et al. (2015) find evidence that the size effect was always existent in the US market. Moreover, they discover that especially the volatile performance of small, low quality or junky firms is responsible for the seemingly non-existent and variable size effect in the 1980s and 1990s. Following and rearranging Gordon and Shapiro (1956)'s growth model, Asness et al. (2014) argue that profitable, growing, safe and shareholder friendly firms are high quality firms and hence, they should command a higher price. The *QMJ* factor is built by sorting stocks and forming portfolios according to a quality score comprising four subcomponent composite measures of profitability, growth, safety and payout. Each composite itself consists of several measures in order to have a robust analysis and to avoid biased results driven by a specific measurement choice.

2.1.2 International Markets

Since the discovery of the size effect in the US market, a large number of studies have been conducted to examine the size effect in other countries or regions. However, looking at international markets involves several challenges. Generally, data histories are substantially shorter compared to the US and data samples are rather small. Furthermore, it has been shown that the size premium seems to be very different when looking at countries individually and varies through time.

Looking at stock returns in the United Kingdom, Dimson and Marsh (1999) confirm the over-performance of smaller companies compared to larger companies in the period from 1955-1997. However, they also find that a shorter, more recent time period from 1989-1997 reverses the size effect leading to an over-performance of larger companies over smaller companies of 6.5% per year. Annaert et al. (2002) investigate the size effect for 15 European countries from 1973-2000 on a country-by-country as well as an European basis. Interestingly, while they report a large and strong size premium of 1.45% per month for the cross-section of European stocks, they do not find a statistically significant size premium anymore when selecting small and big stocks relative to the market size of each country. Heston et al. (1999) also look at the European market using monthly total returns for firms from 12 different countries between 1980 and 1995. They find a significant negative relationship between returns and firm size, which is mainly based on variations in size within each country.

Instead of looking at the European market, Rouwenhorst (1999) examines stocks from 20 emerging equity markets for the time period 1982-1997. He finds similar results as studies focusing on developed markets including a significant size premium of 0.7% per month. Durand et al. (2007) examine the Australian market and find a positive and statistically significant size premium for the period 1990-2001, which is in contrast to evidence of an insignificant and negative size premium in the US and international markets for this time period. In his paper, van Dijk (2011) compares results from different studies regarding the size premium in international markets. He gathers size premia from several studies and reports that a substantial size effect exists in international markets ranging from 0.13% per month in the Netherlands to 5.06% per month in Australia. However, he questions some results and criticizes small datasets, short investigated time periods and different sorting methodologies lacking thorough robustness analyses. Hou et al. (2011) use a comprehensive amount of data comprising 27,488 individual stocks from 49 countries for the period 1981-2003 to study several firm-level characteristics that might explain the cross-sectional and time-series variation in global stock returns. Regarding the size effect, they report a size premium of 0.55% per month. However, they do not find a reliable relation between stock returns and firm size in Fama-MacBeth regression results. More recently, Fama and French (2012) examine stock returns and accounting data for 23 developed countries from 1989-2011, which they combine into the four regions North America, Europe, Japan and Asia Pacific to ensure a sufficient amount of data in each portfolio. They report a monthly size premium of 0.1% globally and 0.24% for North America, but negative size effects of -0.06% for Europe, -0.09% for Japan and -0.21% for Asia Pacific. Except for Japan, they also find that the value premium in average stock returns and spreads in momentum returns decrease with size.

2.1.3 Nordic Markets

So far, no paper has solely focused on the size premium in Nordic countries. However, some studies report results regarding the size effect in Sweden, Norway, Denmark and Finland. Asness et al. (2014) provide their dataset on AQR's online library and report monthly factor returns for 23 developed countries. Using all common stocks on the Compustat/XpressFeed Global database, they show an average monthly size premium for Sweden, Norway, Denmark and Finland from July 1990 to December 2015 of -0.09%, 0.04%, -0.26% and -0.05%, respectively.

2.2 Anomalies of the Size Effect

Despite the aforementioned empirically found variations of the size effect in different time periods and different geographies, the size effect has been challenged at several fronts. Primarily, the so-called January effect or turn-of-the-year effect seems to be the main driver for the size premium. Reinganum (1981), Keim (1983) and Roll (1983) find that in January, mean returns related to size are larger than in the remaining eleven months. Additionally, the relation between abnormal returns and size is always negative and more prominent in January. The January effect is more pronounced in small firms. Contrary, for the UK market, Dimson and Marsh (2001) do not find evidence that the turn-of-the-year effect is related to the relative performance of small versus large companies but is rather related to the overall UK market.

Besides, the size effect seems to be driven by the smallest, microcap stocks. Banz (1981) demonstrates that the size effect is most pronounced for the smallest firms. According to Crain (2011) and Bryan (2014) the size effect is only concentrated among the smallest 5% of firms. Horowitz et al. (2000b) argue that through the removal of the smallest firms with less than five million dollar market value, the size effect disappears and no significant relation can be observed.

Since market value, which is calculated as market price times shares outstanding, is typically used as proxy for size, researchers have claimed that the apparent negative relationship between returns and market value is caused by misspecifications of asset pricing models. Berk (1995, 1996, 1997) argues that even when firm size is not related to returns, market value will be negatively related to returns, because market value is not only measuring size but also a firm's discount rate. For this reason, two firms with the same size might have different market values depending on their riskiness and thus discount rates. The firm with the lower market value will have higher expected returns indeed, even though the two firms have the same size. Furthermore, he shows that non-price based measures including book value of assets, value of property, plant and equipment, annual sales and number of employees do not support the hypothesis of a relation between firm size and average returns.

2.3 Explanations of the Size Effect

Several studies try to identify explanations for the size effect. While some researchers believe in risk-based explanations or suggest that the size effect is a proxy for liquidity, others argue that behavioral biases account for the anomaly. Even though the purpose of this paper is not to test explanations for the size premium, we provide a brief overview of proposed explanations that have been discussed in academic literature.

2.3.1 Risk-based Explanations

While showing that size and the ratio of book-to-market equity (BE/ME) are related to systemic patterns in relative profitability and growth, Fama and French (1993) argue that there is an economic story behind size and book-to-market effects in average stock returns. These systemic patterns might be the source of common risk factors in returns. Contrary, Asness et al. (2015) identify a challenge for risk-based explanations. After controlling for quality, they report a positive size effect which seems to be driven not by small, low-quality firms as a risk story would suggest, but by small high quality firms. Similarly, Fama and French (2015a) propose a new five-factor asset pricing model, but fail to explain average returns of stocks of small firms that have low profitability, but invest heavily anyway. Berk (1995, 1996, 1997) shows that measuring size as market value includes the discount rate of the company and hence, market value is not only a measure of size but also of risk. He argues that a negative relation between risk and market value is implied by this measure.

2.3.2 Liquidity

The size effect is believed to be a proxy for liquidity risk. Since stocks of small companies are traded very infrequently, the liquidity premium is argued to be responsible for the outperformance of stocks of smaller firms compared to stocks of larger firms. Amihud and Mendelson (1986) argue that liquidity is a major driver of the size premium. Amihud (2002) measures illiquidity as the daily ratio of absolute stock return to its dollar volume, averaged over a year. In line with other studies, he shows that expected returns increase in illiquidity. Regarding the size effect, illiquidity seems to affect small firms more strongly which implies that variations in the size effect might be related to changes in market liquidity over time. Even though he finds a negative relation between size and illiquidity, cross-sectional regressions of stock returns on certain variables reveal that loadings on both illiquidity and size are statistically significant leading to the conclusion that size measures more than just illiquidity. However, Amihud et al. (2005) acknowledge that liquidity could help to resolve asset pricing puzzles such as the size effect. Pastor and Stambaugh (2003) also propose their own monthly liquidity measure and find that marketwide liquidity is a factor in explaining returns. Adding a liquidity variable to Fama and French (1993)'s three-factor model, they show that size is not a clear proxy for liquidity, however. Ibbotson et al. (2013) claim that liquidity measured by stock turnover could be an investment style just as size, value/growth and momentum. They do not find that size captures liquidity, though, and report a negative relation between liquidity and size.

Generally, it is not straightforward how to measure liquidity. Investigating the liquidity measure proposed by Ibbotson et al. (2013), the short-term reversal factor following Nagel (2012) and the liquidity risk factor-mimicking portfolio from Pastor and Stambaugh (2003), Asness et al. (2015) point out that many of the liquidity measures are not very correlated to each other indicating noise in measuring liquidity. Moreover, Asness et al. (2015) claim that after controlling for quality, SMB is not subsumed by common liquidity measures.

2.3.3 Behavioral Biases

Another explanation of the size effect is provided by behavioral theory. Lemmon and Portniaguina (2006) investigate the relationship between investor sentiment and the size premium empirically by using consumer confidence as a measure of investor optimism. They show that sentiment does not seem to forecast time-series variation in value and momentum premia, but it does so for small stocks since 1997. Durand et al. (2007) investigate the Australian market from 1990-2001 and draw the conclusion that investors' emotional arousal, proxied by turnover ratio, and disproportionate reactions to arousing stimuli, proxied by momentum, drive the small size effect. Furthermore, van Dijk (2011) claims that investor behavior, which is used to explain the value effect, might as well be used to explain the size effect. As value firms have usually shown poor performance, over-extrapolation of past performance leads to relatively low stock prices for value stocks which eventually yields higher returns once the overreaction is corrected. Since Chan and Chen (1991) find that small firms also tend to perform poorly, van Dijk (2011) argues that overreaction could potentially explain the size effect. Regarding the reverse size effect in the 1980s and 1990s, a behavioral explanation might be investors' preference. Van Dijk (2011) states that investors could just like big stocks and dislike small stocks, though this theory does not explain the apparent variation in the size effect over time.

3 Data and Empirical Methodology

This study is focused on the Nordics in general and primarily analyzes Sweden, which is the largest market in the Nordic region. Hence, our argumentation in this section is centered around the Swedish market but highlights key facts of the other Nordic countries as well. Asness et al. (2015) is the paper closest to ours and therefore, choices concerning methodology are often motivated by comparability reasons. In the following, we explain our dataset, discuss major methodological challenges, define the construction process of portfolios and factors and provide summary statistics.

3.1 Data and General Remarks

Bloomberg serves as our primary data source, supplemented by data from Datastream. We use stock prices and fundamental accounting data for the Nordic countries Sweden, Norway, Denmark and Finland from July 1981 to December 2015. However, caused by a fairly limited data coverage in the early years as well as a required five-year estimation period for certain variables used in the portfolio construction the sample period ranges from July 1986 until December 2015 with the first set of portfolios being constructed at the end of June 1986. In our smallest sample, Finland, factor returns are computed starting in July 1993 due to even higher data limitations. Stocks are allocated to individual countries based on their country of domicile as well as the location of their primary exchange. We only use the major security of a company and for stocks traded in multiple markets, we only use the primary trading vehicle identified by Bloomberg and Datastream. In order to avoid survivorship bias, we include inactive or dead stocks, which are defined as stocks that merged, defaulted or were delisted during our sample period. Furthermore, only common stocks are used in our analyses (as classified by Bloomberg and Datastream) following Asness et al. (2015) and Fama and French (1993). For this reason, depository receipts, exchange-traded funds, real estate investment trusts, closed-end funds and preference shares are excluded. Fama and French (1992) exclude stocks of financial companies and argue that high leverage is normal for these firms and less likely indicates financial distress in comparison to non-financial firms. However, Asness et al. (2015) do not exclude financial companies and in order to be as close as possible to their study, we follow their approach. In addition, disregarding such a large sector as financials would result in a significant sector distortion. As this study aims to explain stock returns of the whole market we consider it consequential to avoid the latter.

Calculated returns are in excess of the one-month U.S. Treasury bill rate, which we use as a proxy for the risk-free rate as do Asness et al. (2015) in their global sample as well. We proceed to build several factors for the four countries. Regarding accounting data, we follow the standard convention used by Fama and French (1992, 1993, 2015a) and Asness et al. (2015) of aligning accounting variables at the end of the firm's fiscal year ending anywhere in calender year *t-1* to June of calendar year *t*. This minimum gap of six months is required because of the lag between a companies' fiscal year end and the availability of annual reports as explained by Fama and French (1992). Generally, we build factors by using independent sorts following Fama and French (2015a) and Asness et al. (2015) in order to avoid that the sorting of the second variable is biased by the first sort on size. However, as do Asness et al. (2015) in their global sample, we also use 2x3 conditional sorts that first sort on size and then on the variable of interest in order to have enough securities in each portfolio. Thus, conditional sorts are likely to be applied in the early years of our sample when the amount of data and stocks is limited, however, with increasing data availability we solely rely on independent sorts to fill all portfolios. These are value-weighted, reconstructed and rebalanced every calendar month.

To avoid exchange rate impacts, portfolio returns for Sweden are in SEK, for Norway in NOK, for Denmark in DKK and for Finland in EUR. In our combined Nordic sample all returns as well as fundamental data are in SEK as Sweden is the biggest market in this area. Thus, we ignore exchange rate risk as do Asness et al. (2015) and Fama and French (2012), which means that we implicitly assume complete purchasing power parity or the impossibility of using the considered assets to hedge exchange rate risk according to Fama and French (2012). Therefore, exchange rate risk potentially poses a problem to our inferences from the analyses of the Nordic sample.

3.2 Breakpoints in the Sort Algorithm

A crucial part in the construction of all factor portfolios is the determination of breakpoints. However, different researchers apply various methodologies in the execution of the same idea. In this section we provide an overview of different approaches and explain our choice of methods.

3.2.1 Size Breakpoints

In a first step the sample is generally sorted on size using market capitalization. When introducing the three factor model, Fama and French (1993) used the median NYSE market value as a size breakpoint and allocate NASDAQ and AMEX stocks to their respective portfolios based on these breakpoints in a subsequent step. This means that Fama and French (1993) disregard the vast amount of rather tiny NASDAQ and AMEX stocks in the size breakpoint determination, which has become common practice for studies covering the US market. The same methodology is applied by many researchers including Asness et al. (2015).

Determining size breakpoints in other markets than the US has proven to be particularly challenging. The underlying idea usually is to approximate the NYSE median, which Fama and French (2012, 2015b) attempt by using size breakpoints that are percentiles of aggregate market value chosen in order to avoid extreme weight on tiny stocks (recall the exclusion of rather tiny NASDAQ and AMEX stocks in the estimation of breakpoints in the US). Thus, stocks in the top 90% of market capitalization are classified as big and stocks in the bottom 10% of market capitalization are classified as small. Asness et al. (2015) apply a different approach and use a percentile of the total number of stocks as a size breakpoint. Following this methodology, after sorting on market value the bottom 80% of stocks are small and the top 20% of stocks are big. In comparison, applying the 10th percentile of aggregate market value as a size breakpoint in a global portfolio formed on size and book-to-market obtained from Kenneth French's website the resulting number of small companies varies between 71% and 86% from July 1990 until December 2015.

Attempting to find a UK equivalent for the NYSE size breakpoint Gregory et al. (2013) use the median market capitalization of the largest 350 stocks. However, other UK studies such as Dimson et al. (2003) use the 70th percentile of all stocks.

Following the original idea of finding a proxy for the NYSE median market value we analyzed percentiles of the total number of stocks (80th, 85th and 90th percentile) as well as percentiles of aggregate market value (10th, 12.5th and 15th percentile) of our Swedish sample and compared the resulting breakpoint market value with the NYSE median market capitalization over our sample period (see Figure 1). According to this analysis, percentiles of total stocks fail to approximate the NYSE median market value for the majority of months in our sample period. In the early years all percentiles overshoot heavily, especially the 90th percentile, and lead to a breakpoint market value, which is up to more than four times the NYSE median market value. Starting around the year 2000 the 90th percentile comes fairly close to the NYSE median, however, the other percentiles result in breakpoint market values that are way below the NYSE median. In contrast, percentiles of aggregate market value seem to provide better proxies of the NYSE median market value and all three different percentiles closely follow the NYSE median over time. In particular, the size breakpoint based on the bottom 12.5% of aggregate market value resembles the NYSE median fairly well and the sum of absolute differences to the NYSE median is lowest of all analyzed breakpoints. For this reason, we define all stocks in the bottom 12.5% of aggregate market value as small. Note that this number is also close to the definition of small cap applied by MSCI, that use the bottom 14% of total market

Figure 1: Monthly Swedish Market Value Size Breakpoints Compared to the NYSE Median Market Value

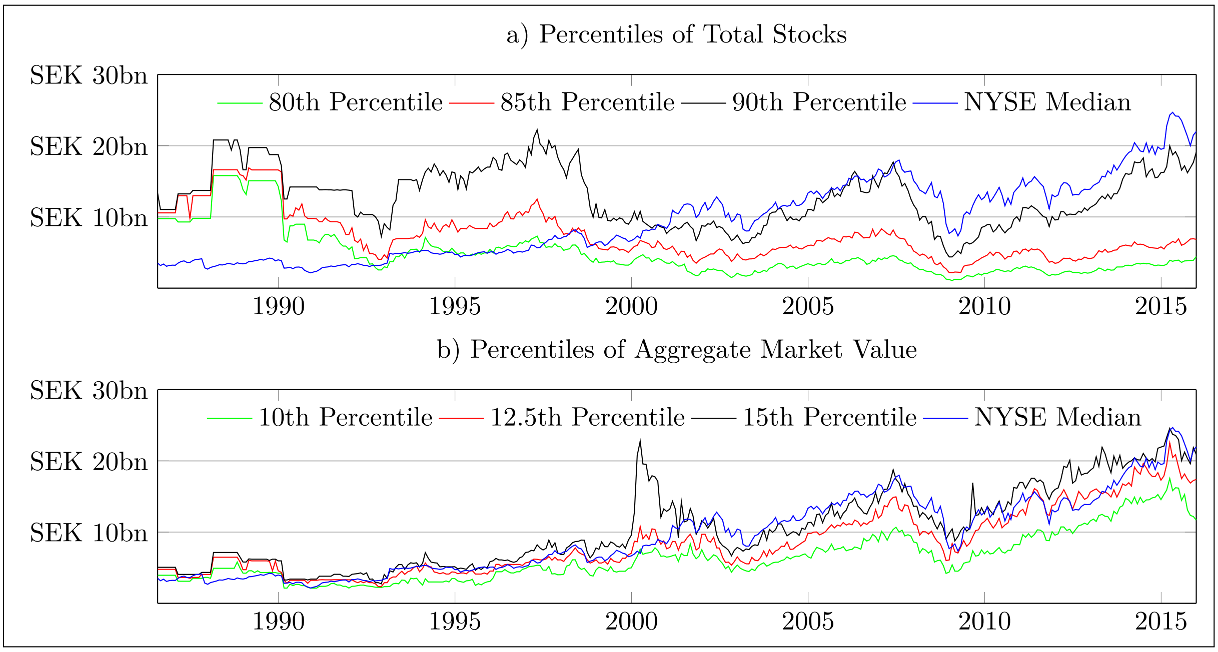

Chart a) shows size breakpoints for market capitalization sorts computed using different percentiles of the total number of stocks in comparison to the NYSE median market value. Chart b) portrays size breakpoints for market capitalization sorts calculated using a percentile of aggregate market value. All breakpoint market values are presented in SEKbn. The NYSE median figures are from Kenneth French's website and are shown in SEKbn using yearly average USD/SEK exchange rates from 1990 to 2015 provided by oanda.com (prior to 1990 the average exchange rate from 1990-2015 is used as no exchange rate is provided earlier).

capitalization for their SmallCap indices, including the MSCI Sweden SmallCap index as well as the MSCI Nordics SmallCap index.

3.2.2 Second Variable Breakpoints

Following the sort on size, Fama and French (1993) also base the sort algorithm for the second variable on NYSE breakpoints in order to avoid sorts that are heavily influenced by the plentiful and tiny AMEX and NASDAQ stocks. In their analyses of global markets Fama and French (2012, 2015b) argue to use big stocks only in the breakpoint estimation of the second variable (e.g. book-to-market and profitability) following their principle to avoid the influence of tiny stocks. However, they do not work with individual countries but combine 23 developed markets into four regions in order to ensure a sufficient amount of securities in each portfolio. Asness et al. (2015), who analyze individual countries in their global analysis, use all stocks to determine the breakpoints for the second variable. In both cases, breakpoints are the 30th and 70th percentile of the considered universe of stocks.

In their studies covering the UK market Gregory et al. (2001, 2003, 2013) base book-to-market breakpoints on the 30th and 70th percentiles of the largest 350 firms. However, Dimson et al. (2003) use the 40th and 60th percentiles.

As we consider individual Nordic countries, the total number of available stocks is naturally lower compared to studies analyzing the US market or regions. For example Fama and French (1993) state that their universe of US stocks comprises 4,797 securities in 1991 already out of which 1,181 are big. In contrast, our sample of Swedish stocks consists of 1,085 stocks that are included in the construction of the market factor at any moment in time with 578 being the maximum and 25 being the minimum number of stocks used in any given month. Moreover, the market factor only requires return data and market values to be available. The amount of stocks used in the construction of all other factors is even lower due to higher data requirements. Considering that up to 92% of companies are classified as small in our Swedish sample, the number of big stocks might not be sufficient for the estimation of breakpoints. For this reason, we follow Asness et al. (2015) and use the whole universe of stocks to calculate breakpoints of all second variables including book-to-market ratios and quality scores.

3.3 Quality Score

We follow Asness et al. (2014) and calculate a single quality score by averaging composite quality measures for *Profitability*, *Growth*, *Safety* and *Payout*, which themselves are averaged z-scores for various measures of quality. In total 21 individual quality characteristics are used to avoid data mining and to obtain a robust measure for the identification of quality stocks, which are defined as stocks of profitable, stable, safe and high payout companies. Z-scores are computed as $z(x) = (r - \mu_r)/\sigma_r$, where x is the variable of interest, r is the vector of ranks, $r_i = rank(x)$, μ_r is the cross-sectional mean and σ_r is the cross-sectional standard deviation of r. Asness et al. (2014) do not state whether a minimum number of individual measures is required in order to calculate a specific composite measure of quality or the final quality score. However, on inquiry Andrea Frazzini[†] kindly let us know that no restrictions are imposed and that each composite is computed as long as one of the measures is available. In order to ensure comparability with Asness et al. (2014, 2015) we apply the same methodology. In the following, the components of each of the four composites are explained. See Asness et al. (2014) for an elaborate description

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of the construction of each measure.

Profitability. Ceteris paribus, stocks of more profitable firms should sell at a higher price. Profitability is measured in terms of profit per unit of book value and the overall profitability z-score is calculated by averaging z-scores of gross profit over assets ($GPoA$), return on equity (RoE), return on assets (RoA), cash flow over assets ($CFoA$), gross profit margin (GPM) and low accruals ($LowAcc$).

$$Profitability = z(z_{GPoA} + z_{RoE} + z_{RoA} + z_{CFoA} + z_{GPM} + z_{LowAcc}) \tag{3.1}$$

$GPoA$ is defined as revenue less cost of goods sold divided by total assets. Net income divided by book equity (total assets) equals RoE (RoA). Book equity (BE) is defined as shareholders' equity minus preferred stock as in Asness et al. (2014, 2015), which is similar to Fama and French (1993). If shareholders' equity is not available we use the sum of common equity and preferred stock. In case this is also not available we use total assets minus total liabilities minus minority interest to proxy shareholders' equity. $CFoA$ is computed dividing cash flow by total assets, where cash flow is defined as the total of net income plus depreciation minus changes in net working capital minus capital expenditure. Working capital is computed as current assets minus current liabilities minus cash and short term investments plus short term debt and plus income taxes payable. GPM is defined as revenue less cost of goods sold divided by total assets. $LowAcc$ equals depreciation less changes in working capital divided by total assets.

Growth. Profit growth is another characteristic that investors are willing to pay for. The growth z-score is computed by averaging z-scores of five-year growth in all six variables used to compute the profitability z-score. Five-year growth is defined as the change in the nominator between year *t* and year *t-5* divided by the denominator of year *t-5*.

$$Growth = z(z_{\Delta GPoA} + z_{\Delta RoE} + z_{\Delta RoA} + z_{\Delta CFoA} + z_{\Delta GPM} + z_{\Delta LowAcc}) \tag{3.2}$$

Safety. Return-based and fundamental-based measures of safety are combined to reflect safe stocks with low required returns that command a higher price. The safety z-score is computed by averaging z-scores of low beta (BAB), low idiosyncratic volatility ($IVOL$), low leverage (LEV), Ohlson's O-Score (O), Altman's Z-Score (Z) and low earnings volatility ($EVOL$).

$$Safety = z(z_{BAB} + z_{IVOL} + z_{LEV} + z_O + z_Z + z_{EVOL}) \tag{3.3}$$

BAB equals minus market beta, which is estimated using rolling one-year standard deviations and rolling five-year three-day correlations following Frazzini and Pedersen (2014). $IVOL$ refers to a stock's idiosyncratic volatility and is calculated from rolling one-year standard deviations of daily beta-adjusted excess returns, skipping the most recent trading day. LEV is computed as minus total debt divided by total assets, where total debt is defined as the total of long term debt, short term debt, minority interest and preferred stock. The bankruptcy risk measures Ohlson's O-Score and Altman's Z-Score are computed following Asness et al. (2014), which is similar to Ohlson (1980) and Altman (1968). $EVOL$ is the standard deviation of annual RoE over the last five years.

Payout. Management determines the fraction of profits distributed among shareholders and reduces agency problems through higher dividends according to Jensen (1986). Thus payout can be interpreted as a measure of shareholder friendliness. The payout z-score is computed by averaging z-scores of net equity issuance ($EISS$), net debt issuance ($DISS$) and total net payout over profits ($NPoP$).

$$Payout = z(z_{EISS} + z_{DISS} + z_{NPoP}) \tag{3.4}$$

$EISS$ is defined as minus one-year percentage change in split-adjusted shares outstanding. $DISS$ is minus one-year percentage change in total debt and $NPoP$ is calculated as the sum of net income minus changes in BE over the past five years divided by the sum of gross profits over the past five years.

Quality. We combine the four quality composites into one quality score by averaging the individual composites.

$$Quality = z(z_{Profitability} + z_{Growth} + z_{Safety} + z_{Payout}) \tag{3.5}$$

3.4 Factors

This section introduces all factors that are employed in our set of regressions later on and describes the construction of each factor's underlying portfolios.

Market. The market factor is calculated as the value-weighted return of all securities per country in our data sample in excess of the one-month US Treasury bill rate, which we obtain from AQR's online data library. This data in turn is sourced from the CRSP as well as the Compustat/XpressFeed Global databases.

Small minus big. Asness et al. (2015) follow Fama and French (1993) in their construction of the SMB factor and therefore, we apply the same methodology. For each of the four Nordic countries, we first rank all stocks by their market capitalization as of the end of June and form two size portfolios consisting of small and big stocks, respectively. In order to proxy the NYSE median market value as closely as possible we use the 12.5th percentile of aggregate market value as explained above. Thus, small stocks are the bottom 12.5% and big stocks are the top 87.5% of aggregate market value of stocks ranked by their market capitalization. We continue by ranking stocks by their book-to-market equity ratio. The BE/ME breakpoints are the 30th and 70th percentile of all stocks. Growth stocks are those in the bottom 30% of BE/ME, value stocks are those in the top 30% and neutral stocks are those between the 30th and 70th percentile. We use the book value of equity of the fiscal year ending in calendar year *t-1*, while market capitalization is used from December of year *t-1* following Fama and French (1993). In order to be included in our analysis companies are required to have positive book equity. After the two independent sorts, stocks are allocated to portfolios depending on their small/big and growth/neutral/value identification leading to six size and BE/ME sorted portfolios. In order to ensure a sufficient number of stocks in each portfolio we also use conditional sorts if independent sorts fail to fill individual portfolios caused by limited data availability in early years. In this mechanism, after the first sort by market capitalization each of the two size portfolios is sorted by BE/ME, again leading to six size and BE/ME sorted portfolios. The portfolios are value-weighted and rebalanced every calendar month to maintain value weights. Finally, the *SMB* factor is the equally-weighted average return of the three small portfolios minus the equally-weighted average return of the three big portfolios.

$$\begin{aligned} SMB \ &= \frac{1}{3}\ (Small\ Value + Small\ Neutral + Small\ Growth) \\ &- \ \frac{1}{3}\ (Big\ Value + Big\ Neutral + Big\ Growth) \end{aligned} \tag{3.6}$$

Value minus growth. We form the *HML* factor following Fama and French (1992) as the equally-weighted average return of the two value portfolios minus the equally-weighted average return of the two growth portfolios, which are derived as described above. Asness and Frazzini (2013) show that in the US market using more-current prices is superior to the standard method of using prices at fiscal year-end in the construction of the *HML* factor. However, for Sweden the dataset available on AQR's online data library shows a superior performance of the *HML* factor constructed using the Fama and French (1992) methodology. Moreover, Asness et al. (2015) rely on the *SMB* factor and *HML* factor provided on Kenneth French's website and thus we construct both factors following Fama and French (1992) to make our results comparable.

$$HML \;=\; \frac{1}{2}\left(Small\ Value + Big\ Value\right) \;-\; \frac{1}{2}\left(Small\ Growth + Big\ Growth\right) \quad (3.7)$$

Momentum. Jegadeesh and Titman (1993) find that stocks with higher returns in the previous 12 months tend to have higher future returns. We follow Kenneth French's website and use a similar methodology as before to build the momentum factor *MOM* that captures the outperformance of recent winner stocks. After sorting on size, we independently rank stocks according to cumulative prior returns from months *t-12* to *t-2* and again use 30th and 70th percentile as breakpoints. In contrast to the construction of *SMB* and *HML*, market values are refreshed every month similar to the momentum factor provided on Kenneth French's website, which is used by Asness et al. (2015). The intersection of the two independent sorts on size and prior returns leads to six portfolios. The *MOM* factor is the equally-weighted average return of the two high return, or *winner*, portfolios minus the equally-weighted average return of the two low return, or *loser*, portfolios.

$$MOM \;=\; \frac{1}{2}\left(Small\ High + Big\ High\right) \;-\; \frac{1}{2}\left(Small\ Low + Big\ Low\right) \quad (3.8)$$

Short-term reversal. Similar to the momentum factor *MOM*, we independently sort on size and prior returns to obtain the short-term reversal factor *STREV*. However, this factor refers to a long-short portfolio that is constructed by ranking stocks according to the past return of the most recent month *t-1*. In contrast to the momentum factor, the short-term reversal factor is the equally-weighted average return of the two low return portfolios minus the two high return portfolios.

$$STREV \;=\; \frac{1}{2}\left(Small\ Low + Big\ Low\right) \;-\; \frac{1}{2}\left(Small\ High + Big\ High\right) \quad (3.9)$$

Quality minus junk. We follow Fama and French (1992, 1993, 1996), Asness and

Frazzini (2013) and Asness et al. (2014) in the construction of the quality factor *QMJ* and sort all stocks independently on size and quality at the end of each calendar month. Therefore, we use the quality score introduced earlier. Quality breakpoints are the 30th and 70th percentile of the whole universe of stocks. The intersection results in six portfolios formed on size and quality, which are value-weighted, refreshed and rebalanced every month. The *QMJ* factor is long the two high-quality portfolios and short the two low-quality (junk) portfolios.

$$QMJ \;=\; \frac{1}{2}\left(Small\ Quality + Big\ Quality\right) \;-\; \frac{1}{2}\left(Small\ Junk + Big\ Junk\right) \quad (3.10)$$

Furthermore, we also build factor portfolios based on the individual components of the overall quality score. Therefore, we rank all stocks independently on size and one of the quality composite scores $Profitability$, *Growth*, $Safety$ and *Payout*, and compute the four factor returns in the same way as the *QMJ* factor returns.

Liquidity. We form decile portfolios by ranking stocks on annual turnover following Ibbotson et al. (2013). Turnover is defined as the cumulative trading volume over the last 12 months divided by the number of shares outstanding. Monthly factor returns (*LIQ*) equal the returns of the lowest liquidity decile minus the returns of the highest liquidity decile.

Furthermore, we compute the liquidity risk factor-mimicking portfolio $LIQRISK$ following Pastor and Stambaugh (2003). For this reason, innovations in liquidity are constructed first. Afterwards, monthly returns are regressed on innovations in liquidity and the Fama and French (1993) three-factor model in order to estimate liquidity betas. See Pastor and Stambaugh (2003) for a detailed description of the calculations. Monthly decile portfolios are formed by ranking on the obtained historical liquidity betas and factor returns are computed as the value-weighted return of the highest liquidity risk decile portfolio minus the lowest liquidity risk portfolio.

Fama and French (2015a) five-factor model. We also compute the profitability factor *RMW* (robust minus weak) and the investment factor *CMA* (conservative minus aggressive), which have been introduced by Fama and French (2015a) in their five-factor model. The factors are constructed similarly to the other Fama and French factors by independent 2x3 sorts on size and a second variable, which are operating profitability (*RMW*) and investment (*CMQ*). Operating profitability is defined as operating income divided by book equity and investment is the annual percentage change in total assets.

$$RMW = \frac{1}{2}\left(Small\ Robust + Big\ Robust\right) - \frac{1}{2}\left(Small\ Weak + Big\ Weak\right) \quad (3.11)$$

$$\begin{aligned} CMA = & \frac{1}{2}\left(Small\ Conservative + Big\ Conservative\right) \\ & - \frac{1}{2}\left(Small\ Aggressive + Big\ Aggressive\right) \end{aligned} \quad (3.12)$$

3.5 Size and Quality Sorted Portfolios

Studying factor portfolios, observed relationships might be caused by the behavior of extreme stocks only and therefore, we also construct decile portfolios as well as a set of 5x5 portfolios in order to analyze any patterns in size and quality.

Decile Portfolios. We create two sets of decile portfolios, which are sorted on size and quality, respectively. In both cases each decile contains 10% of the total number of companies. Furthermore, we construct a factor from size decile portfolios, which is long the smallest size decile and short the biggest size decile (*P1-P10*).

5x5 Portfolios. Following Fama and French (2015b) and Asness et al. (2015), we also construct 25 size-quality sorted portfolios from independent 5x5 sorts. Fama and French (2015b) use the 3rd, 7th, 13th and 25th percentiles of aggregate market values as size breakpoints whereas Asness et al. (2015) use quintiles by number of companies. We follow the latter in order to ensure a high degree of comparability. Finally, the breakpoints for quality are every 20th percentile by total number of companies. The portfolios are refreshed and rebalanced on a monthly basis.

3.6 Summary Statistics

Table 1 reports summary statistics for each of the individual countries Sweden, Norway, Denmark and Finland as well as for the combined Nordic sample. For comparability reasons all market values are reported in SEKm. Sweden is the largest market with 1,391 stocks that are included at any point in our sample period and accounts for roughly half (49%) of the Nordic market with 2,829 stocks in total. Out of these, 64% are inactive as of December 2015 and the percentage of dead stocks ranges from 50% in Finland to 76% in Norway. In all samples mean equal-weighted returns are negative over the whole sample period with the exemption of Finland. Furthermore, returns of the sample starting in 2000 are lower compared to the earlier sample period, which is likely explained by the

Table 1: Summary Statistics

	Total	Active	Dead
Panel A: Sweden			
Number of Stocks	1,391	578	813
Mean EW Return 1986-2015	-0.70%	-0.21%	-1.67%
Mean EW Return 1986-1999	-0.27%	0.04%	-0.40%
Mean EW Return 2000-2015	-1.07%	-0.42%	-2.74%
Mean MV 1995 (SEKm)	5,564	7,489	4,564
Mean MV 2005 (SEKm)	8,871	13,484	2,179
Mean MV 2015 (SEKm)	9,807	9,807	/
Panel B: Norway			
Number of Stocks	684	162	522
Mean EW Return 1986-2015	-0.75%	-0.09%	-1.55%
Mean EW Return 1986-1999	-0.41%	-0.03%	-0.52%
Mean EW Return 2000-2015	-1.04%	-0.13%	-2.42%
Mean MV 1995 (SEKm)	2,169	4,280	1,342
Mean MV 2005 (SEKm)	7,357	13,660	1,807
Mean MV 2015 (SEKm)	9,935	9,935	/
Panel C: Denmark			
Number of Stocks	471	147	324
Mean EW Return 1986-2015	-0.45%	-0.18%	-1.07%
Mean EW Return 1986-1999	-0.45%	-0.39%	-0.49%
Mean EW Return 2000-2015	-0.44%	-0.01%	-1.57%
Mean MV 1995 (SEKm)	1,943	2,795	1,464
Mean MV 2005 (SEKm)	8,476	11,794	2,283
Mean MV 2015 (SEKm)	22,464	22,464	/
Panel D: Finland			
Number of Stocks	263	131	132
Mean EW Return 1993-2015	0.23%	0.36%	-0.25%
Mean EW Return 1993-1999	0.83%	1.07%	0.68%
Mean EW Return 2000-2015	-0.01%	0.07%	-0.63%
Mean MV 1995 (SEKm)	2,869	3,789	2,223
Mean MV 2005 (SEKm)	12,737	15,748	3,793
Mean MV 2015 (SEKm)	12,976	12,976	/
Panel E: Nordics			
Number of Stocks	2,829	1,019	1,810
Mean EW Return 1986-2015	-0.55%	-0.12%	-1.41%
Mean EW Return 1986-1999	-0.28%	-0.06%	-0.39%
Mean EW Return 2000-2015	-0.77%	-0.17%	-2.27%
Mean MV 1995 (SEKm)	3,192	4,577	2,455
Mean MV 2005 (SEKm)	9,033	13,590	2,236
Mean MV 2015 (SEKm)	12,061	12,061	/

The table reports summary statistics for the Nordic countries Sweden, Norway, Denmark and Finland as well as for the Nordic region. Statistics are shown for all available common stocks as well as for active and dead stocks separately. Presented are the number of stocks, equally weighted (EW) average monthly returns for the whole sample period from July 1986 until December 2015 as well as for the sub-periods 1986-1999 and 2000-2015, and December average market values (MV) for the years 1995, 2005 and 2015. Returns are calculated from local currency and market values are in SEKm. Due to limited data for early years, the sample period for Finland ranges from July 1993 to December 2015.

occurrence of several large crisis events including the dot.com bubble, the financial crisis 2007-2009 and the European sovereign debt crisis.

Returns of dead stocks are significantly lower in comparison to active stocks and dead stocks feature a lower average market value. It seems natural that successful companies perform well and grow in terms of market value over time whereas unsuccessful companies show poor returns and low market values until they eventually vanish. Therefore, the aforementioned differences in returns and market values appear logical. Moreover, Table 1 indicates the importance of including dead stocks when analyzing asset pricing models in order to avoid survivorship bias. Note, that the sum of stocks included in individual countries is not equal to the number of stocks included in the Nordic sample. While the time period of the Finish sample is 1993-2015 due to data limitations, we include data from a few additional Finish stocks that went inactive prior to 1993 in the Nordic sample.

4 Empirical Results

The Swedish market is our object of investigation throughout this section and we present results for the other Nordic countries later on as a robustness check. First, we untangle the interaction of size and quality and demonstrate return patterns by examining size decile and quality decile portfolios as well as by looking at 25 independently sorted size and quality portfolios. In a second step we utilize a multi-factor model in order to explain returns of portfolios with varying size and quality characteristics. Therefore, we start by reporting general characteristics of the factors we constructed in the Swedish market. Then, we solely focus on the small-minus-big factor following Fama and French (1993) and test whether controlling for quality resurrects the size premium in the Swedish market as shown by Asness et al. (2015) in the US market. In addition, we analyze seasonality patterns and liquidity effects. In the final part, we dissect the quality-minus-junk factor into its components and individually analyze the intersection of small/big stocks and quality/neutral/junk stocks and show that the most extreme stocks in terms of small size and junk pose the greatest challenge to current asset pricing models.

4.1 Return Patterns Among Size and Quality Sorted Portfolios

4.1.1 Decile Portfolios Sorted on Size

Table 2 reports summary statistics for decile portfolios that are built by sorting all firms according to market value and forming ten portfolios containing 10% of all Swedish stocks each for the time period of our data sample from July 1986 to December 2015. Portfolio P1 consists of the 10% of firms with the lowest market capitalization and portfolio P10 contains the 10% of firms with the highest market capitalization.

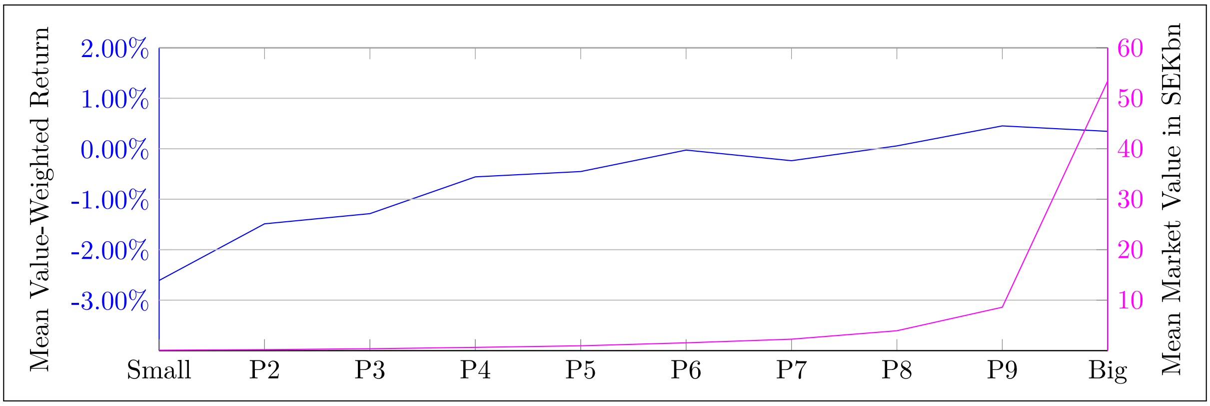
Table 2: Characteristics of Size Decile Portfolios

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P1-P10
VW Return	-2.61%***	-1.49%***	-1.29%***	-0.56%	-0.45%	-0.03%	-0.24%	0.06%	0.45%	0.35%	-2.95%***
	(-4.45)	(-3.09)	(-3.25)	(-1.07)	(-1.12)	(-0.07)	(-0.60)	(0.13)	(1.24)	(0.91)	(-5.30)
EW Return	-1.20%**	-1.31%***	-1.28%***	-0.79%	-0.74%*	-0.18%	-0.48%	-0.09%	0.42%	0.36%	-1.56%***
	(-2.25)	(-3.01)	(-3.17)	(-1.45)	(-1.85)	(-0.48)	(-1.17)	(-0.23)	(1.09)	(0.97)	(-3.01)
σ	11.02%	9.06%	7.45%	9.78%	7.56%	7.02%	7.43%	8.14%	6.90%	7.16%	10.49%
Sharpe Ratio	-0.237	-0.164	-0.173	-0.057	-0.060	-0.004	-0.032	0.007	0.066	0.048	-0.282
Avg. MV	85	200	378	648	961	1,548	2,270	3,942	8,603	53,436	
Avg. Quality	-0.157	-0.112	-0.063	-0.061	-0.020	0.032	0.052	0.053	0.067	0.075	

*significance at the 10% level **significance at the 5% level ***significance at the 1% level
The table presents summary statistics for 10 portfolios based on annual market capitalization sorts in June and containing 10% of the total number of Swedish common stocks each. Depicted are monthly value-weighted (VW) average returns and the corresponding standard deviations (σ) and Sharpe ratios, monthly equally-weighted average returns (EW), average market values (MV) in SEKm and the average quality scores for each size decile.

The first row of Table 2 shows monthly average value-weighted portfolio returns, which are also plotted in Figure 2. A nearly monotonic pattern between returns and size is observable. Interestingly, only the three largest deciles P8, P9 and P10 show positive mean returns. Portfolio P1 has the lowest value-weighted average return of -2.61% and portfolio P10 has a value-weighted average return of 0.35%. Based on the $P1-P10$ decile spread, this leads to a significant negative size effect of -2.95% questioning the existence of a small size premium in Sweden. The second row reports monthly equally-weighted average returns for each size decile portfolio. Though not to such a strong extent, average equally-weighted returns show the same pattern as average value-weighted returns. The size effect is still significantly negative at -1.56%. Most interestingly, while returns of high market value portfolios do not change that much with regard to the two methods (see portfolios P9 and P10), the average return of portfolio 1 changes from -2.61% using value-weighting to -1.20% using equal-weighting. Apparently, firms in portfolio 1 with relatively high market values have lower returns than firms with the lowest market values. Thus, the observed pattern of nearly monotonically increasing returns with size among decile portfolios does not hold within the smallest decile portfolio, i.e. among micro-cap stocks. This finding is in support of Bryan (2014) and Crain (2011) who argue that the size effect is concentrated among the smallest 5% of firms.

Figure 2: Monthly Mean Return and Market Capitalization of Size Decile Portfolios

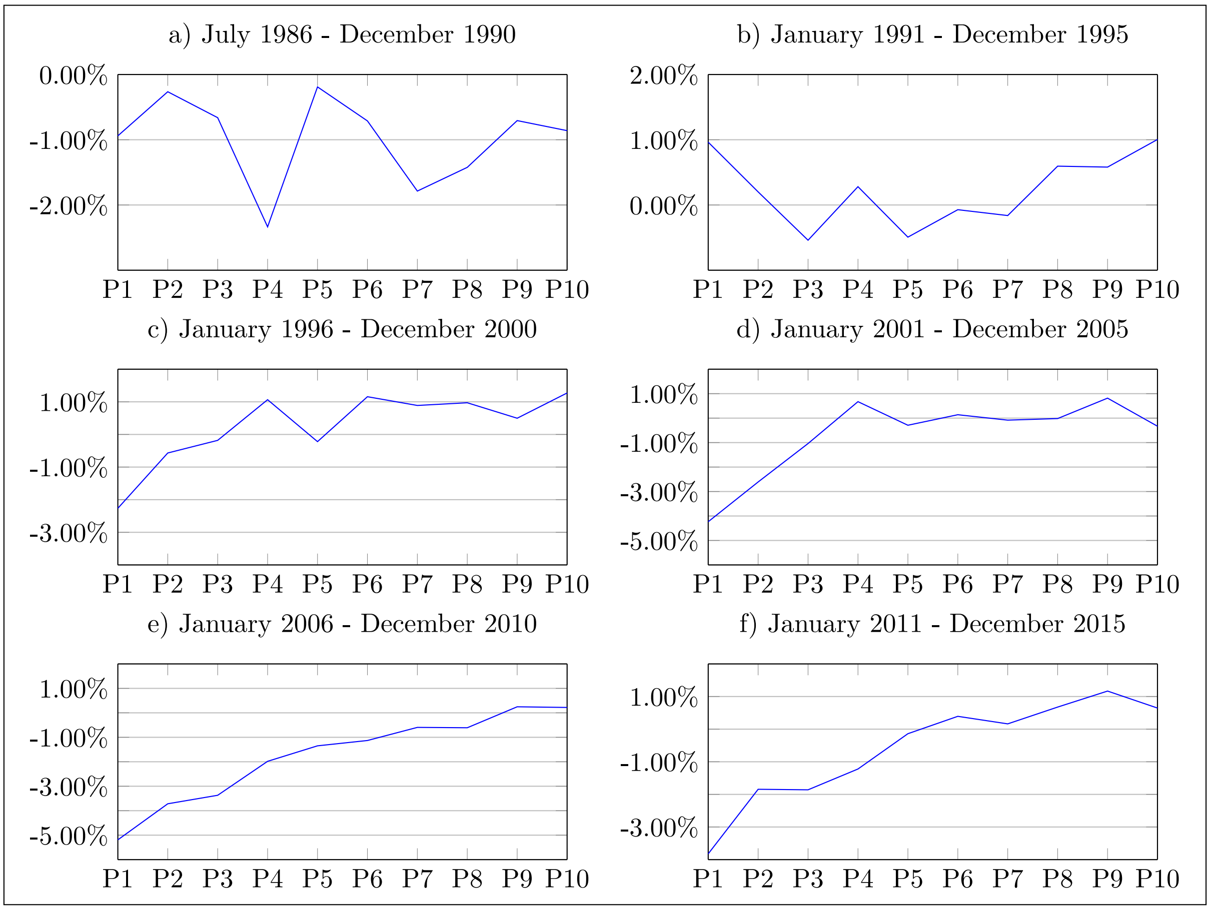


The figure plots average value-weighted monthly returns in percent and average market values in SEKbn of every size decile portfolio obtained from sorting all Swedish common stocks on market capitalization every June.

Looking at size decile returns of five-year periods from 1986 until 2015 portrayed in Figure 3 reveals that the identified close to monotonic relationship between size and returns roughly holds for the most recent four five-year periods starting in 1996. However, in the earlier periods no clear pattern is observable and it seems that this relationship emerged at some point around the turn of the millennium and was reinforced ever since. Only looking at rolling one-year returns of the smallest ($P1$) and largest size decile ($P10$) portfolios supports this finding and shows that starting roughly in 2000, $P10$ persistently outperforms $P1$, which provokes the emergence of a significant negative $P1 - P10$ decile spread (see Appendix A1).

A risk-based theory of the size effect explains the anomaly with higher relative risk inherent to smaller firms. As reported in Table 2, standard deviation is highest for the portfolio containing the smallest companies. Taking returns and risk into consideration, the fourth row of Table 2 reports the monthly Sharpe ratio of each size decile. Again, a clear pattern shows that firms with high market values are preferable to firms with low market values. The results point out challenges for risk based explanations as already shown by Asness et al. (2015) and Fama and French (2015a) who face difficulties in

Figure 3: Value-Weighted Monthly Mean Returns of Size Deciles for Five-Year Periods



This figure plots average value-weighted monthly returns for 10 size decile portfolios obtained from June market capitalization sorts using all Swedish common stocks. P1 contains the 10% of stocks with lowest market values and P10 the 10% with highest market values. Chart a) shows mean returns for the period from July 1986 until December 1990 and charts b) to f) present mean returns for consecutive five-year periods until December 2015.

explaining average returns on subsets of small stocks, particularly small junk stocks. Similarly, in our case small cap stocks show the lowest returns and highest risk measured by standard deviation, which is the opposite of what a risk story would suggest.

The fifth row of Table 2 states average market values of each size decile. Naturally, market value increases with each size decile since we sorted all stocks according to market value when forming the portfolios. However, this analysis points out how big large stocks are compared to small stocks measured in terms of market capitalization, which is also portrayed in Figure 2. The largest 10% of stocks account for 74% of aggregate market value and adding the second largest size decile adds another 12% leaving the smallest eight size deciles with 14% of the total market capitalization.

Lastly, the sixth row of Table 2 displays average quality scores for each size decile.

Interestingly, a perfect monotonic relationship between quality and size can be observed. The smallest firms with regard to market value have the lowest quality scores and thus can be referred to as *junk* firms. This finding is in line with Asness et al. (2015) who find that small firms are more likely to be junk stocks than large firms. Similarly, the largest companies seem to comprise more high quality firms. As we observe a *reverse* size effect or positive relation between size and returns one should keep the quality pattern in mind as *QMJ* and *SMB* premia could potentially just measure the same effect in the Swedish market, however, we are showing that this is not the case.

4.1.2 Decile Portfolios Sorted on Quality

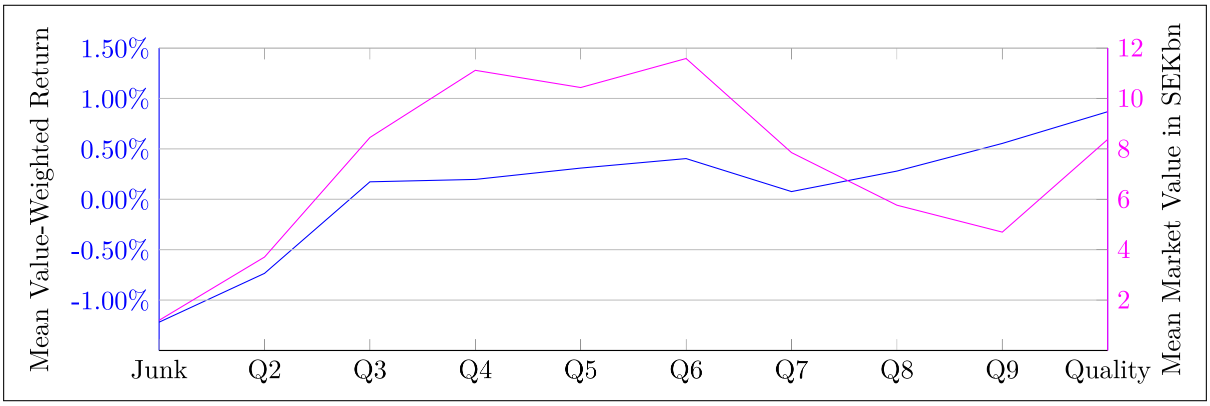
Table 3 reports summary statistics for quality decile portfolios. Instead of sorting according to market value, we sort on quality scores (see Equation 3.5) introduced by Asness et al. (2014) and form ten portfolios containing 10% of the total number of companies each. Value-weighted decile returns, which are plotted in Figure 4, show an increasing return pattern leading to a significantly positive quality-minus-junk effect of 2.09% on a monthly basis. Looking at mean value-weighted quality decile returns of five-year periods from 1986 until 2015 emphasizes this finding (see Appendix A2). Equally-weighted returns confirm the pattern, however, equally-weighted returns are generally lower than value-weighted returns especially for the lowest quality portfolio. Hence, the larger set of stocks in each quality decile has higher average returns, again indicating the existence of a negative or *reverse* size premium. The quality-minus-junk effect is again substantial and significantly positive at 2.45% per month when considering equally-weighted returns.

Table 3: Characteristics of Quality Decile Portfolios

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q10-Q1
VW Return	-1.22%**	-0.73%	0.17%	0.20%	0.31%	0.40%	0.08%	0.28%	0.55%	0.87%**	2.09%***
	(-2.44)	(-1.41)	(0.31)	(0.43)	(0.75)	(1.06)	(0.18)	(0.71)	(1.46)	(2.35)	(4.43)
EW Return	-2.52%***	-1.67%***	-0.85%**	-0.19%	-0.18%	-0.05%	0.02%	0.12%	0.10%	-0.07%	2.45%***
	(-4.40)	(-3.16)	(-2.00)	(-0.49)	(-0.51)	(-0.13)	(0.06)	(0.32)	(0.26)	(-0.19)	(5.17)
σ	9.39%	9.81%	10.42%	8.59%	7.77%	7.15%	8.02%	7.42%	7.15%	6.95%	8.87%
Sharpe Ratio	-0.130	-0.075	0.017	0.023	0.040	0.057	0.010	0.038	0.078	0.125	0.235
Avg. MV	1,198	3,707	8,451	11,117	10,434	11,586	7,852	5,765	4,697	8,375	
Avg. Quality	-0.905	-0.314	-0.154	-0.065	-0.005	0.061	0.123	0.197	0.303	0.642	

*significance at the 10% level **significance at the 5% level ***significance at the 1% level
The table presents summary statistics for 10 portfolios based on quality score sorts containing 10% of the total number of Swedish common stocks each. Depicted are monthly value-weighted (VW) returns and the corresponding standard deviations and Sharpe ratios, monthly equally-weighted returns (EW), average market values (MV) in SEKm and the average quality score per quality decile.

Figure 4: Monthly Mean Return and Market Capitalization of Quality Decile Portfolios



The figure plots the average value-weighted monthly return in percent and the average market capitalization in SEKbn of every quality decile portfolio obtained from sorting all Swedish common stocks on quality scores every month following Asness et al. (2014).

A clear pattern between standard deviation and quality is not observable. Nevertheless, note that firms with the highest quality witness the lowest standard deviation on average and deciles Q1, Q2 and Q3 that comprise the lowest quality stocks feature the highest standard deviations. Sharpe ratio is positively related to quality and thus, high quality firms seem to be a preferable investment. Portfolio Q1 observes the lowest monthly Sharpe ratio of -0.13 and portfolio Q10 observes the highest monthly Sharpe ratio of 0.13. Generally, Sharpe ratios increase with quality similarly to value-weighted returns. Only portfolios Q7 and Q8 face slightly lower returns and Sharpe ratios that constitute a minor violation of the identified increasing pattern.

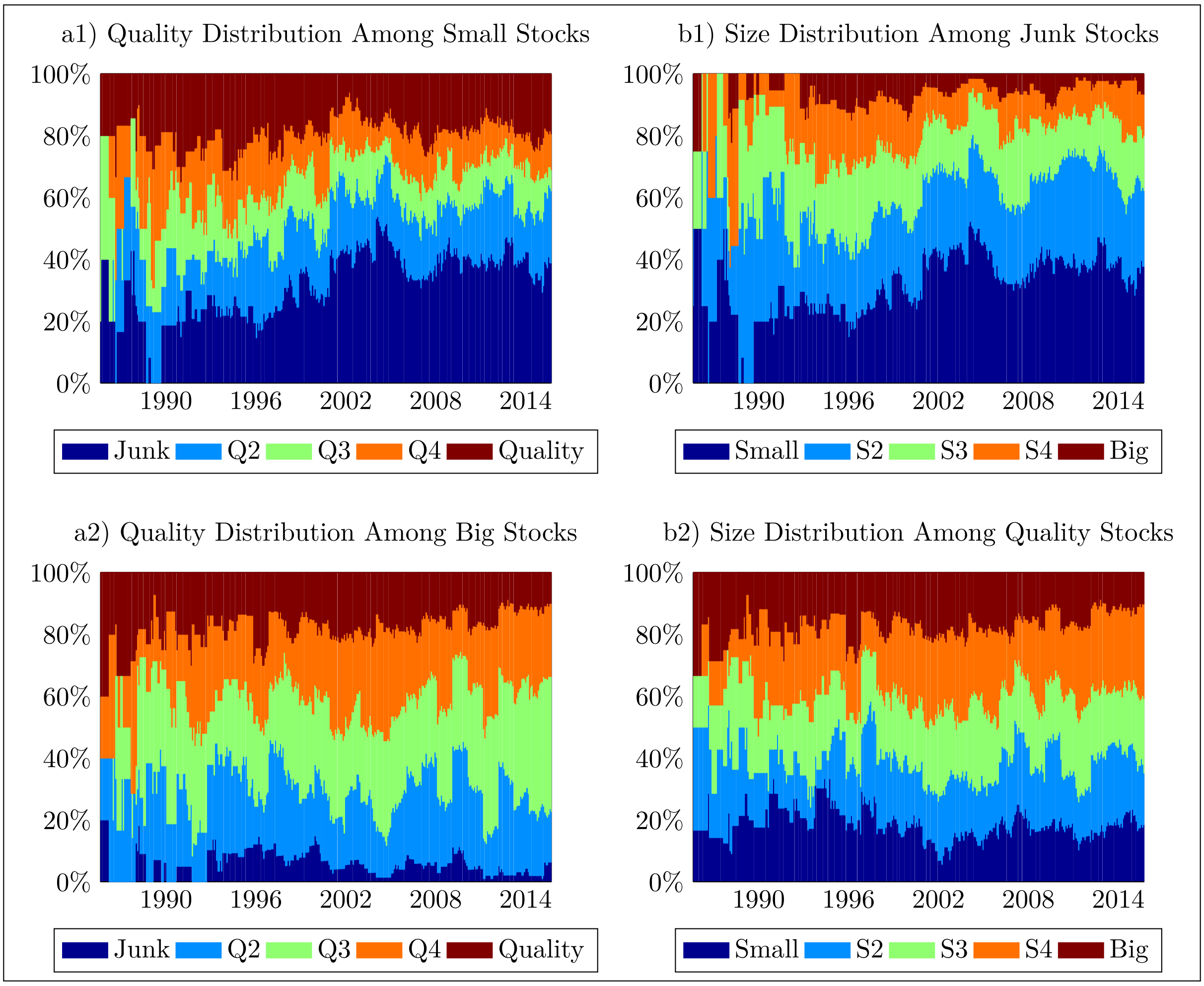
Interestingly, average market value is lowest at 1.2bn SEK for the lowest quality or junk portfolio. However, a clear monotonic pattern between size and quality scores is not observed as portfolios Q4, Q5 and Q6 show the highest mean market capitalization. Nevertheless, the average market value of the highest quality decile portfolio is considerably higher at 8.4bn SEK than the average market value of the junk portfolio. As shown in Figure 4, this might hint at a positive relation between size and quality. Especially, a relationship between small stocks and junk is indicated.

4.1.3 Two-way Sort: 5x5 Size and Quality Sorted Portfolios

The previous analyses established a relationship between size and quality and raise the question whether the two effects measure the same phenomenon. In order to further investigate this conjuncture, we form 25 portfolios based on independent size and quality sorts following Fama and French (1993)'s 5x5 sorting methodology. As in Asness et al. (2015)

we use quintiles in our size and quality sorts leading to five quality and size portfolios, respectively, of which each contains 20% of all Swedish stocks. Since we use independent sorts, however, the number of stocks in each of the 25 size-quality sorted portfolios can vary quite considerably.

Figure 5: Size and Quality Distribution Among Stocks in the Extreme Quality and Size Quintile Portfolios



The Figure shows size and quality distribution among Swedish common stocks within quintile portfolios obtained from two independent sorts on market capitalization and quality score, respectively. Each sort divides the universe of stocks in portfolios containing 20% of the total number of stocks. Charts a1) and a2) portray the quality distribution in quintiles with the smallest and largest stocks. Charts b1) and b2) depict the size distribution in quintiles with lowest (junk) and highest (quality) quality scores.

Figure 5 shows the quality distribution among the smallest and largest quintiles of stocks as well as the size distribution among the lowest and highest quality quintiles. The percentage of junk among small stocks is as high as 54% and amounts to 32% on average. In contrast, only 5.6% of big stocks are junk on average. Reversing the analysis and looking at the size distribution among junk and quality stocks reveals a similar picture. The share of small stocks in the lowest quality quintile is substantially higher than the share of small stocks in the highest quality quintile. Moreover, larger stocks are considerably more likely to be of higher quality than junk. Looking at the other three size and quality quintiles (see Appendix A3) reveals that these patterns are persistent and not just observable in the extreme quintile portfolios. The average percentage of junk stocks per size quintile decreases monotonically with size and the average percentage of small stocks per quality quintile decreases with increasing quality.

Table 4 shows average monthly value-weighted excess returns for each of the 25 portfolios. Looking at returns of quality quintiles, we observe a relationship between size and quality. Although the pattern is not perfectly monotonic, within each quality quintile returns tend to increase with size. The result is a significantly negative small-minus-big premium. This premium is huge in absolute terms generally and by far the largest in the junk quintile. It is staggering that returns of small stocks are persistently negative and that returns of big stocks are positive in all quality quintiles.

Table 4: Monthly Mean Excess Returns of 25 Portfolios Formed on Size and Quality

	Small	2	3	4	Big	Small - Big
Junk	-3.23%***	-2.38%***	-1.83%***	-1.31%**	0.19%	-3.42%***
	(-5.23)	(-3.57)	(-3.45)	(-2.47)	(0.34)	(-5.06)
2	-0.79%	-1.39%***	-0.49%	-0.49%	0.25%	-1.04%
	(-1.50)	(-2.73)	(-1.09)	(-0.92)	(0.53)	(-1.51)
3	-1.52%***	-0.65%	-0.13%	-0.01%	0.36%	-1.88%***
	(-2.90)	(-1.20)	(-0.27)	(-0.01)	(0.89)	(-3.60)
4	-1.04%**	0.17%	0.36%	0.50%	0.35%	-1.39%***
	(-1.98)	(0.37)	(0.91)	(1.17)	(0.80)	(-2.64)
Quality	-0.94%*	-0.64%	0.17%	0.81%*	0.67%*	-1.61%***
	(-1.74)	(-1.24)	(0.41)	(1.92)	(1.89)	(-3.07)
Quality - Junk	2.29%***	1.74%***	2.00%***	2.12%***	0.47%	
	(4.10)	(2.60)	(4.93)	(5.04)	(0.91)	

*significance at the 10% level **significance at the 5% level ***significance at the 1% level
The table reports results from time-series regression tests of 25 portfolios sorted on size (market capitalization) and quality/junk as defined by Asness et al. (2014). The set of 25 portfolios is obtained by independently sorting all Swedish common stocks into five size and quality quintiles. Reported are average monthly excess returns for each portfolio with respective t-statistics in parentheses.

Moreover, returns show a tendency to increase with quality within each size quintile, but again this pattern is not completely monotonic. The resulting spreads between returns of the quality and junk quintiles are consistently positive. Except for the portfolio consisting of stocks with the highest market values, a statistically significant positive quality-minus-junk premium exists which is highest for the smallest stocks and lowest for the biggest stocks. Therefore, we conclude that size and quality do not measure the same effect, though they are positively correlated. In contrast, Asness et al. (2015) find a negative relationship between size and quality, which can be explained by the *reverse* size effect occurring in the Swedish market. Furthermore, Table 4 shows that especially average returns in the upper left corner, which comprises small junk stocks, are statistically significant and seem to be the highest in absolute terms. This suggests that both the *reverse* size effect as well as the quality effect are mainly driven by these stocks. In addition, the biggest and highest quality stocks show significant returns at the 10% significance level contributing to the *reverse* size and quality-minus-junk effect.

4.2 Multi-Factor Explanations of the Size Anomaly

Previously, we investigated the return behavior of size and quality sorted portfolios and established a positive relationship between the two effects. In this section, we explain returns of the SMB factor using a multi-factor model. For this reason, we perform several sets of regressions involving the Fama and French (1993) factors MKT and HML, the lagged market factor MKT_{t-1}, the momentum factor MOM and the quality factor QMJ. First, we explain our choice of factor model and report summary statistics for the factor portfolios. Then, we start to analyze the size effect in our full sample period as well as in two sub-periods and show the impact of controlling for quality. Afterwards, we investigate seasonality effects and look at January and non-January months separately. In the final section we test the relationship between the size effect and liquidity.

4.2.1 Long-Short Factor Portfolios

In order to explain returns of various portfolios with different size and quality characteristics, we use a six-factor model that utilizes the factors MKT, its lagged value, SMB, HML, MOM and QMJ. The choice of factors is not arbitrary but follows Asness et al. (2015) and ensures comparability to their results.

This model adds the lagged market factor to the Fama and French (1993) three-factor model in order to capture delayed price reactions, particularly of small stocks, to market-wide news. This approach follows the results of Lo and MacKinlay (1988), Hou and Moskowitz (2005) and Asness et al. (2001) and accounts for non-synchronous price responses caused by liquidity differences and lead-lag effects among stocks according to Asness et al. (2015). Fama and French (2015a) point out that HML is redundant in the presence of MKT, SMB and their newly introduced quality factors CMA and RMW.

Table 5: Summary Statistics of Monthly Factor Portfolios

	Total Stocks	Minimum Stocks	Max Stocks	Average Stocks	Average Return (t-statistic)	Standard Deviation	Sharpe Ratio
MKT	1085	25	578	302	0.29% (0.79)	6.78%	0.0422
SMB	969	24	486	265	-0.18% (-0.77)	4.42%	-0.0411
HML	969	14	292	159	0.61%* (1.70)	6.78%	0.0905
MOM	988	14	302	165	1.42%*** (3.51)	7.60%	0.1863
QMJ	1051	14	330	177	0.86%*** (2.79)	5.81%	0.1484

*significance at the 10% level **significance at the 5% level ***significance at the 1% level
Total stocks refers to the number of Swedish stocks for which required data is available to build the market factor (MKT), small-minus-big or size factor (SMB), high-minus-low or value factor (HML), momentum factor (MOM) and quality-minus-junk factor (QMJ). Minimum, maximum and average stocks refer to stocks per month that are included in the factor portfolios. Average return is calculated as the average of value-weighted monthly returns and standard deviation measures the dispersion of monthly returns. Sharpe ratio is shown in its monthly form as well. T-statistics of average returns are presented in parenthesis.

Nonetheless, they acknowledge that the value factor should be included if one is interested in portfolio tilts toward size, value, profitability and investment premiums. Furthermore, Asness (2014) argues that value is all but redundant in the presence of momentum as they work best together. The latter already provides an argument for the inclusion of the momentum factor MOM. Fama and French (2015a) justify the exclusion of momentum with its large independence to other factors as MOM is poorly explained by other factors measured in terms of R-square. In addition, it reflects an attempt to limit dimensionality. In opposition, Asness (2014) argues that while disregarding momentum is not harmful for the explanation of cross-sectional portfolio returns, it is, however, peculiar from a practical industry perspective as real world portfolios are built on the momentum factor as well. Moreover, the creation of largely uncorrelated or ideally negatively correlated strategies that deliver significant alphas might essentially reflect the paramount desire of investors. Lastly, the quality factor QMJ is added. The consideration of a quality dimension has gained traction and represents state-of-the-art research. Popular examples are the investment (CMA) and profitability (RMW) factors in Fama and French (2015a)'s five-factor model as well as the QMJ factor introduced by Asness et al. (2014).

Table 5 reports summary statistics for the *MKT*, *SMB*, *HML*, *MOM* and *QMJ* factors in the Swedish market. In total approximately 1,000 stocks are included in all factor portfolios at any point in time with a minimum of 14 stocks and a maximum of 578 stocks being used simultaneously. Figure 6 shows that the number of stocks included in each portfolio increases over time with a few setbacks during and after major crisis events. Naturally, significantly more stocks are part of the MKT and *SMB* factors as all other factors exclude stocks that fall between the 30th and 70th percentile breakpoints in the sort on the second variable. Moreover, *Growth* is constructed using less stocks in comparison to all other quality factors as a five-year period of data availability is required.

Figure 6: Total Number of Stocks Included in Various Factor Portfolios per Month

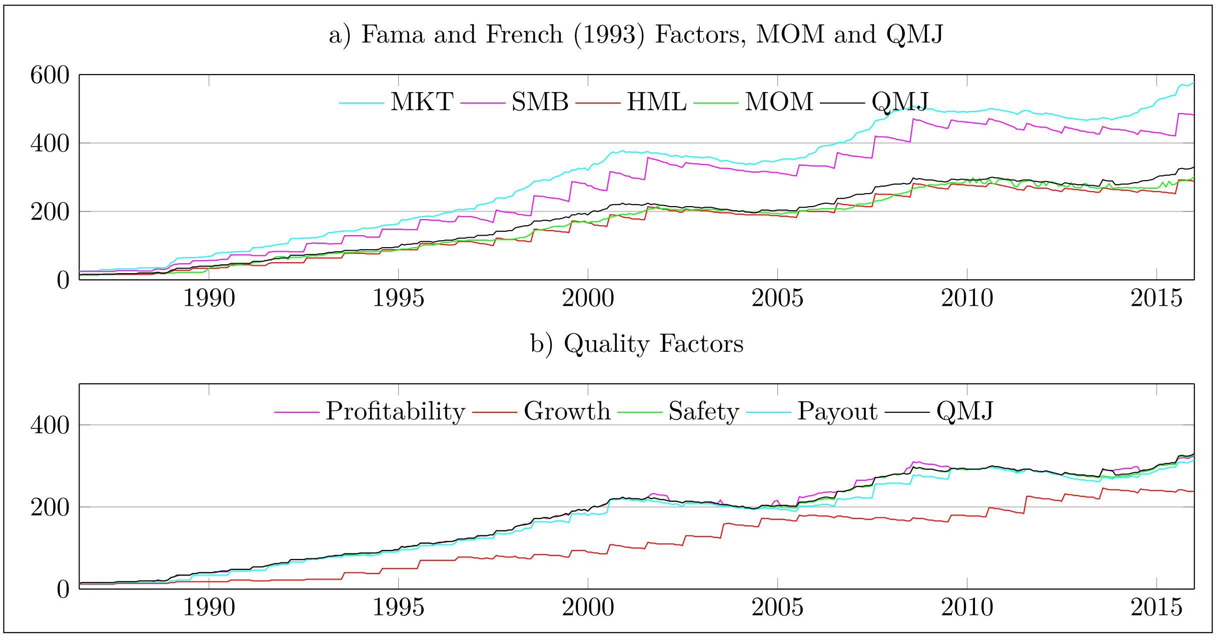
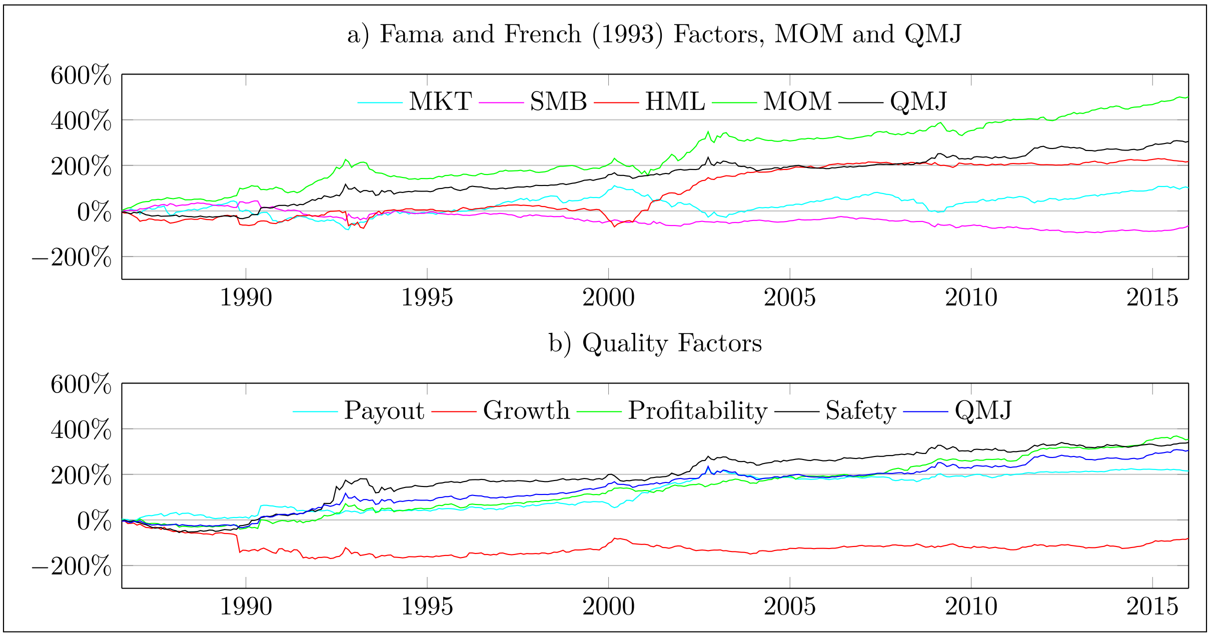


Chart a) shows the number of Swedish common stocks that are included to calculate monthly market (MKT) factor returns, small-minus-big (SMB) factor returns, high-minus-low (HML) factor returns, momentum (MOM) factor returns and quality-minus-junk (QMJ) factor returns. Chart b) displays the number of Swedish common stocks per month that are included in the QMJ factor portfolio and the four quality factor portfolios $Profitability$, $Growth$, $Safety$ and $Payout$.

In addition, Table 5 shows average monthly returns as well as the corresponding monthly standard deviations and Sharpe ratios for each factor. The cumulative performance from July 1986 until December 2015 is portrayed in Figure 7. Interestingly, only the momentum factor MOM and the quality factor QMJ show significant average returns at the 1% significance level. The average monthly return of *SMB* equals -0.18% (-2.18% p.a.) and it is the only factor that performed worse than the market, which shows an average monthly return of 0.29% (3.43% p.a.). MOM performed best in our sample with an average monthly return of 1.42% (16.99% p.a.) and a monthly Sharpe ratio of 0.1863.

Looking at quality factors, the average monthly return of *QMJ* amounts to 0.86% (10.35% p.a.). All other quality factors with the exemption of *Growth* also perform very well and fairly similar. In contrast, *Growth* seems to be a weak measure of quality and the cumulative performance is negative resulting in a monthly mean return of -0.23%.

Figure 7: Cumulative Performance of Factor Portfolios



The Figure portrays the cumulative performance of several factor portfolios in the Swedish market from July 1986 until December 2015. Returns are in percent and summed up on a monthly basis. Chart a) shows the performance of the market (MKT), small-minus-big (SMB), high-minus-low (HML), momentum (MOM) and quality-minus-junk (QMJ) factors. Chart b) compares returns of QMJ to the performance of the quality factors $Profitability$, $Growth$, $Safety$ and $Payout$.

Consequently, *QMJ* is the least correlated with *Growth* (see Appendix A4). Only *Payout* and *Growth* are slightly negatively correlated, reflecting a natural relationship between higher payout and lower growth, which is similar to the findings of Asness et al. (2014) in the US market. These results confirm that also in the Swedish market quality firms tend to be of high quality with respect to several different aspects of quality supporting the creation of a robust composite quality measure by combining all quality characteristics.

4.2.2 The Size Effect Controlling for Quality

Table 6 shows results of time series regressions for the size premium (SMB) on different sets of factors. In order to allow for comparison with Asness et al. (2015) we split the full sample into two sub-periods and perform regressions using the full sample from July 1986 until December 2015 as well as the sub-period samples. The first sub-period ranges from July 1986 until December 1999, which resembles the so-called *Embarrassment* period in Asness et al. (2015). The second sub-period starting in January 2000 is similar to the period Asness et al. (2015) name *Resurrection*. The underlying idea of this division into sub-periods is to independently analyze periods of different performances of the size effect. In the 1980s and 1990s the size premium was shown to have delivered a poor performance

Table 6: The Size Effect Controlling for Quality

Panel A: Adding QMJ

$$SMB_t = \alpha + \beta MKT_t + \beta_{-1} MKT_{t-1} + hHML_t + mMOM_t + qQMJ_t + \epsilon_t$$

	α	β	β_{-1}	h	m	q	R^2
Full Sample	-0.0013	-0.1765***					0.0732
(1986-2015)	(-0.58)	(-5.27)					
	-0.0016	-0.1918***	0.1092***				0.1006
	(-0.71)	(-5.75)	(3.27)				
	0.0003	-0.2105***	0.1207***	-0.1750***	-0.0529*		0.1758
	(0.11)	(-6.03)	(3.74)	(-5.50)	(-1.71)		
	0.0016	-0.2465***	0.1192***	-0.1652***	0.0137	-0.2567***	0.2687
	(0.75)	(-7.39)	(3.92)	(-5.50)	(0.44)	(-6.65)	
Sub-Period 1	-0.0015	-0.2409***					0.1061
(1986-1999)	(-0.35)	(-4.36)					
	-0.0017	-0.2529***	0.0782				0.1167
	(-0.42)	(-4.53)	(1.38)				
	-0.0000	-0.2520***	0.1014*	-0.2373***	-0.1884***		0.2430
	(0.01)	(-4.33)	(1.91)	(-4.73)	(-2.89)		
	0.0030	-0.2856***	0.1105**	-0.1984***	-0.1125*	-0.3836***	0.4035
	(0.84)	(-5.48)	(2.34)	(-4.40)	(-1.90)	(-6.48)	
Sub-Period 2	-0.0009	-0.0937**					0.0323
(2000-2015)	(-0.41)	(-2.52)					
	-0.0011	-0.1120***	0.1491***				0.1158
	(-0.53)	(-3.11)	(4.22)				
	-0.0003	-0.1293***	0.1494***	-0.0756*	0.0112		0.1302
	(-0.13)	(-3.12)	(4.22)	(-1.70)	(0.40)		
	0.0002	-0.1540***	0.1464***	-0.0927**	0.0324	-0.0740	0.1406
	(0.08)	(-3.46)	(4.14)	(-2.03)	(1.02)	(-1.50)	

continued on next page

Table 6: (continued)

Panel B: Subcomponents of QMJ

$$SMB_t = \alpha + \beta MKT_t + \beta_{-1} MKT_{t-1} + hHML_t + mMOM_t + qQ_t + \epsilon_t$$

	α	β	β_{-1}	h	m	q	R^2
Q = *Profitability*	0.0031	-0.1996***	0.1040***	-0.1834***	-0.0309	-0.3058***	0.3044
	(1.49)	(-6.21)	(3.50)	(-6.26)	(-1.08)	(-8.02)	
Q = *Growth*	-0.0001	-0.1961***	0.1211***	-0.1674***	-0.0529*	-0.1044***	0.1965
	(-0.03)	(-5.63)	(3.80)	(-5.30)	(-1.73)	(-2.99)	
Q = *Safety*	0.0014	-0.2601***	0.1223***	-0.1900***	0.0089	-0.1838***	0.2285
	(0.64)	(-7.37)	(3.92)	(-6.13)	(0.27)	(-4.87)	
Q = *Payout*	0.0009	-0.2273***	0.1116***	-0.1546***	-0.0430	-0.1301***	0.1934
	(0.39)	(-6.48)	(3.48)	(-4.77)	(-1.39)	(-2.75)	

Panel C: Fama and French (2015a) Five-Factor Model

$$SMB_t = \alpha + \beta MKT_t + \beta_{-1} MKT_{t-1} + hHML_t + mMOM_t + rRMW_t + cCMA_t + qQ_t + \epsilon_t$$

	α	β	β_{-1}	h	m	r	c	q	R^2
Full Sample	0.0011	-0.2242***	0.1107***	-0.1454***	-0.0547*	-0.0531	-0.1102**		0.1894
(1986-2015)	(0.49)	(-6.26)	(3.43)	(-4.27)	(-1.70)	(-1.33)	(-2.10)		
Q = *QMJ*	0.0022	-0.2484***	0.1079***	-0.1300***	-0.0017	0.0288	-0.1692***	-0.2891***	0.2936
	(1.06)	(-7.38)	(3.57)	(-4.08)	(-0.06)	(0.73)	(-3.40)	(-7.15)	
Q = *Profitability*	0.0032	-0.1958***	0.0990***	-0.1685***	-0.0442	0.0250	-0.0803*	-0.3088***	0.3112
	(1.56)	(-5.89)	(3.31)	(-5.34)	(-1.49)	(0.65)	(-1.65)	(-7.82)	
Q = *Profitability*	0.0034	-0.2014***	0.0982***	-0.1651***	-0.0402		-0.0832*	-0.3021***	0.3103
	(1.63)	(-6.28)	(3.29)	(-5.31)	(-1.39)		(-1.72)	(-7.93)	

*significance at the 10% level **significance at the 5% level ***significance at the 1% level

The table presents time series regressions of monthly SMB premia on different sets of factors. T-statistics are shown in parenthesis. The factors are constructed using all Swedish common stocks. Panel A shows regressions on the market factor MKT, its lagged value, the value factor HML, the momentum factor MOM and adds the quality factor in a final step. Regressions are performed for the full sample period from July 1986 to December 2015 and two sub-periods 1986-1999 and 2000-2015. Panel B shows regressions controlling for quality with one of the subcomponents of QMJ, which are the composite quality measures $Profitability$, $Growth$, $Safety$ and $Payout$. In Panel C, SMB is regressed on the Fama and French (2015a) five-factor model, QMJ and $Profitability$.

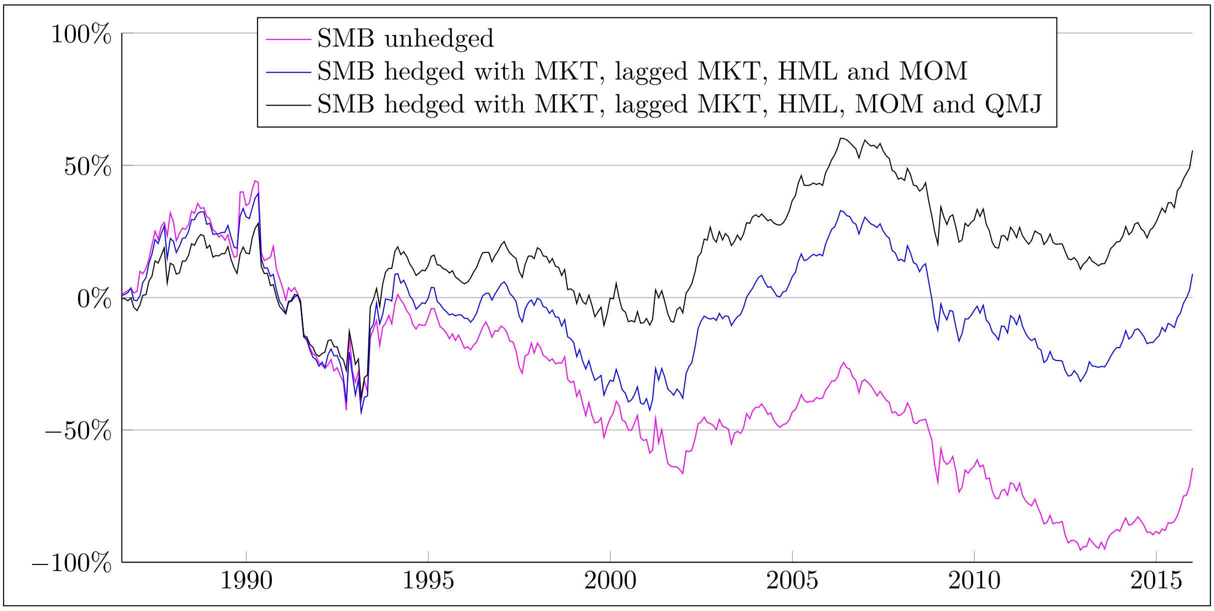
and after 2000 it suddenly seemed to have reappeared, at least in the US market. For each sample period we regress *SMB* on *MKT*, the lagged market factor, *HML*, *MOM* and control for quality by adding *QMJ* in a final step.

Regressing *SMB* on *MKT* delivers a negative alpha of -0.13% over the full sample period from July 1986 to December 2015. Adding the lagged market factor, which accounts for potential lags in pricing especially of smaller and less-liquid stocks, has a negative impact on alpha, which now amounts to -0.16%. The coefficient on the lagged market return is significantly positive with a t-statistic of 3.27. Including the *HML* and *MOM* factors pushes alpha up to 0.03% and SMB has a significantly negative coefficient on *HML* with a t-statistic of -5.50. The coefficient on *MOM* is negative as well but only significant at the 90% confidence level with a t-statistic of -1.71. The precision of the *SMB* premium is raised by controlling for the Fama and French (1993) factors (excluding *SMB*) and *MOM*, which is demonstrated by an R-square of 17.6%, compared to an R-square of 10.0% when only controlling for the market factor and its lagged return. However, no size premium is visible as alpha is very close to zero.

The fourth row shows results of the regression including *QMJ*. The first fundamental observation is that controlling for quality raises alpha to 0.16%. This is an increase of 29 bps compared to controlling only for *MKT*. Compared to controlling for the Fama and French (1993) factors and *MOM*, *QMJ* is able to push up alpha by another 13 bps. The coefficient on *QMJ* is significantly negative with a t-statistic of -6.65, meaning that small stocks tend to be rather junky. Controlling for this exposure to junk partially restores a positive *SMB* premium in the Swedish market. Figure 8 depicts the cumulative performance of *SMB* unhedged, *SMB* hedged with the market, its lagged value, *HML* and *MOM* as well as *SMB* hedged with all of the previous factors including *QMJ*. Clearly, hedging *SMB* for its exposure to junk positively affects performance.

The second interesting observation is that controlling for quality substantially increase the precision of the *SMB* premium as R-square increases by 9.3% to 26.9%. These findings are similar to Asness et al. (2015) who report an increase in alpha amounting to 39 bps in the US market after controlling for quality. However, even though adding *QMJ* to the regression also increases alpha by substantial amounts and raises it to a positive level, in contrast to Asness et al. (2015) alpha is still not statistically different from zero in our Swedish sample. Thus, we can confirm that controlling for quality has a strong and similar effect in the Swedish market as in the US market but the size premium is still not significant in statistic terms.

Figure 8: Cumulative Performance of SMB and SMB Hedged



The Figure plots the cumulative sum of returns over time of SMB unhedged, SMB hedged with the market, its lagged value, HML and MOM and SMB hedged with all of the previous including QMJ. All factors are constructed using all Swedish common stocks and returns are computed using full sample estimates of betas on all factors (see Table 6).

Looking at the two sub-periods reveals a similar picture compared to the analysis of the full sample. In the sample including data before 2000 the impact of QMJ is strongest and alpha rises to 0.30% compared to -0.15% when controlling for MKT only and -0.00% when controlling for the Fama and French (1993) factors and MOM. The regression including QMJ significantly increases precision again and shows an R-square of 40.4%, compared to 24.3% when controlling for the Fama and French (1993) factors and MOM. The coefficient on QMJ is significant with a t-statistic of -6.48 and the coefficient on MOM is not significant anymore when controlling for quality. In the sub-period 2000-2015, precision of the SMB premium is lowest of all regressions with an R-square of 14.1% after controlling for quality. The size premium can still be raised from -0.09% when controlling for the market factor only to 0.02% when adding the Fama and French (1993) factors, MOM and QMJ. However, in this sub-period adding QMJ is only able to raise alpha by another 5 bps compared to the regression using the Fama and French (1993) factors and MOM. The coefficient on QMJ is not significant with a t-statistic of -1.50.

Controlling for quality by adding one of the four composite measures used to compute the QMJ factor yields similar results as shown in panel B of Table 6. The loading on quality is very significant and negative in all cases and alpha rises compared to the regression controlling for *MKT* only. Especially, controlling for *Profitability* substantially raises alpha to 0.31%, which is even higher compared to controlling for *QMJ* and only marginally insignificant with a t-statistic of 1.49. However, controlling for *Growth* lowers alpha compared to controlling for the Fama and French (1993) factors and MOM. The finding that *Growth* is the weakest measure of quality is consistent with Asness et al. (2014, 2015).

Fama and French (2015a) introduced profitability and investment factors in their five-factor model and intuitively, these parameters are related to a firm's quality. The profitability factor is based on a sort on operating profitability and hence, similar to characteristics used in the *QMJ* factor. Moreover, conservatism in investment, measured as annual asset growth, is more prone to quality firms and this characteristic is strongly related to the *Payout* factor according to Asness et al. (2014). Asness et al. (2015) state that the two additional Fama and French factors also measure quality to some extent. However, according to Fama and French (2015a) stock returns of small firms with low profitability but high investment activity pose a problem to their asset pricing model.

Panel C of Table 6 reports regression results of *SMB* on different Fama and French factors and *QMJ*. Indeed adding *RMW* and *CMA* to the Fama and French (1993) three-factor model (excluding *SMB*) plus *MOM* raises alpha from 3 bps to 11 bps. This confirms that the two new factors are related to quality and junk. The coefficients on profitability and investment are negative as found by Asness et al. (2015), meaning that small firms tend to show low profitability and invest rather aggressively. However, the loading on profitability (RMW) is not statistically significant. Moreover, adding *QMJ* to the Fama and French five-factor model significantly increases alpha by 11 bps to 0.22% and substantially raises precision as R-square increases by more than 10%. The loading on *RMW* turns positive and decreases in absolute terms indicating that *QMJ* captures the explanatory power of *RMW* on the size premium. *RMW* appears to be a weaker measure of quality than the composite measure *QMJ* consisting of 21 individual quality characteristics. In contrast to Asness et al. (2015) the loading on investment is not reduced by adding *QMJ* but even more negative and significant. Additionally, controlling for the Fama and French quality factors raises *SMB* alpha by 6 bps compared to only controlling for *QMJ* indicating that the investment factor *CMA* might capture something that is not explained by *QMJ*. Nevertheless, we can confirm that controlling for the Fama and French factors CMA and RMW, which capture some quality components, has a similar effect on SMB alpha compared to controlling for QMJ. Moreover, we find that controlling for all three quality factors restores an even higher size premium amounting to 22 bps, although still statistically not significant with a t-statistic of 1.06. The increase in alpha is primarily driven by a significant negative exposure to CMA, which is even reinforced through the presence of QMJ.

The next step combines our findings that the simpler quality factor $Profitability$ seems to fare better in resurrecting the size premium than QMJ and that the investment factor CMA likely captures a further quality component not soaked up by QMJ. Row 3 in Panel C of Table 6 reports regression results for SMB on the Fama and French (2015a) five-factor model and $Profitability$. Alpha now amounts to 32 bps with a t-statistic of 1.56 and hence is not particularly higher compared to only controlling for $Profitability$ but more significant in statistic terms. The loading on investment is still significant at the 10% signifiance level but heavily soaked up by $Profitability$. The coefficient on RMW is again insignificant. This factor is constructed using sorts on operating profitability and therefore, captures one component included in the $Profitability$ factor following Asness et al. (2014). For this reason, we drop the RMW factor in row 4, which reinforces significance of CMA and $Profitability$. Most interestingly, alpha amounts to 34 bps and is almost statistically significant at the 10% significance level with a t-statistic of 1.63.

In conclusion, we show that quality persistently restores the size premium economically, however, the definition and measurement of quality matters. Generally, QMJ raises SMB alphas and in particular $Profitability$ fares well in restoring a positive size premium. The Fama and French investment factor CMW seems to add another quality component that is not soaked up by QMJ and the combination delivers a size premium with highest statistical significance. Nevertheless SMB returns are still all but reliable different from zero, even after controlling for quality.

4.2.3 Seasonality Patterns in the Size Premium

In the previous section we have shown that controlling for quality has an economically significant impact on SMB. Because the size effect has been claimed to merely be a January effect we are interested in analyzing seasonality effects and split our sample in a January sample and a sample comprising the months from February to December.

Panel A of Table 7 reports summary statistics of *SMB* and *P1-P10* returns of the full and seasonal sample for our full sample period as well as the two sub-periods. SMB returns are positive in January over the full sample period, which is caused by a massive size premium in the period starting in the year 2000. In the remaining months of the year the average size premium is negative regardless of the analyzed period. This could lead to the conclusion that the reappearance of a size effect since 2000, which has been pointed out in academic research, for instance by Asness et al. (2015), is solely explained by the reappearance of the January effect. However, there is still a *reverse* size effect in Sweden since 2000 with nearly monotonic return patterns, which we have shown earlier. Note that SMB returns are never statistically significant, which might seem surprising, especially in case of the substantial 1.57% January return in the period 2000-2015. Considering the short length of our overall sample period and that the January series naturally contains only one observation in every given year might contribute to the low statistical significance.

Table 7: Seasonal Summary Statistics of SMB and the P1-P10 Decile Spread Factor

	Panel A: SMB		**Panel B: P1-P10**	
	Average Return (t-statistic)	Standard Deviation	Average Return (t-statistic)	Standard Deviation
Full Sample	-0.18% (-0.77)	4.42%	-2.95%*** (-5.30)	10.49%
- January	0.84% (1.01)	4.44%	3.46% (1.42)	13.12%
- Feb.-Dec.	-0.27% (-1.11)	4.41%	-3.53%*** (-6.33)	10.04%
1986-1999	-0.28% (-0.65)	5.55%	-0.28% (-0.40)	9.02%
- January	-0.07% (-0.05)	4.76%	0.38% (0.23)	5.83%
- Feb.-Dec.	-0.30% (-0.65)	5.63%	-0.34% (-0.45)	9.25%
2000-2015	-0.10% (-0.42)	3.18%	-5.21%*** (6.49)	11.11%
- January	1.57% (1.51)	4.17%	5.97% (1.43)	16.71%
- Feb.-Dec.	-0.25% (-1.08)	3.05%	-6.22%*** (-8.32)	9.92%

*significance at the 10% level **significance at the 5% level ***significance at the 1% level
The table reports average monthly returns and standard deviations of the SMB factor (Panel A) and the $P1 - P10$ factor (Panel B), which is the size decile spread between portfolios with the smallest and largest market values. Both factors are constructed in the Swedish market. T-statistics are shown in parentheses.

Panel B shows summary statistics for the $P1 - P10$ factor, which is long the smallest 10% of stocks and short the largest 10% of stocks. In contrast, the SMB factor is built using all stocks. For this reason, the size effect is substantially amplified and the average return amounts to a significant -2.95% per month for the full sample. Interestingly, size premia are rather small before 2000 and in similar domains than SMB returns in that period (with the exception of a positive January premium for $P1 - P10$) but this picture vigorously twists in the later period. An enormous January premium of almost 6% is juxtaposed by an absolutely even higher negative size premium throughout the rest of the year resulting in a significant negative size effect of -5.21%.

Finally, we investigate seasonality effects in the size premium while controlling for several factors including quality. Therefore, we regress SMB on the market, its lagged value, HML, MOM as well as dummy variables for January and for the remaining months, respectively. In a second step we add QMJ to the regression. Results of these regressions are reported in Table 8. Looking at results involving the full sample period reveals that controlling for quality lowers alpha in January by 11 bps and increases alpha in the rest of the year by 15 bps. Thus, controlling for quality lowers the return difference between January and the non-January months to 96 bps. A similar tendency was observed by Asness et al. (2015). However, they show that controlling for quality restores the size effect in the non-January months in the US market. In our Swedish sample SMB returns still seem to be characterized by almost no performance in the non-January months and a substantial outperformance in January. Note however, that even the January premium is still not statistically significant. In the following we show that separately analyzing the sub-periods before and after 2000 solves this mystery and uncovers the source of significant January returns.

Considering the period before 2000, the impact of quality seems to be even more impressive as alpha in January declines from 81 bps to 20 bps and increases in the non-January months from -7 bps to 31 bps. Hence, controlling for quality completely removes the January effect in this period. In contrast, alpha even increases by 6 bps to 1.49% in January in the period 2000-2015 and alpha in the remaining months is raised by 5 bps to -12 bps. Earlier we found that there is a nearly monotonic reverse size effect in this period as well as a strong January premium. Controlling for quality even increases the January premium compared to the regression without QMJ and most interestingly the January premium is now significant with a t-statistic of 1.99. The impact of quality is lower in this period and consequently, the loading on quality is not as strongly negative as in the earlier period and not statistically significant although the t-statistic is still fairly high in absolute terms amounting to -1.54.

In conclusion, the seasonality analysis discovers that positive SMB returns after controlling for quality are solely driven by statistically significant January returns since 2000, which are not explained by exposure to junk. In the period until the millennium, a supposedly high and economically significant January premium of 81 bps as well as the apparent underperformance of SMB during the rest of the year is mostly explained by loading on junk. Thus, we show that January does not feature higher returns compared to the remaining months in the period 1986-1999 if quality is considered. Furthermore, we again observe a shift in return patterns occurring during our sample period. Earlier we showed

Table 8: Seasonality Patterns in the Size Effect

$$SMB_t = \alpha_{Jan.} + \alpha_{Non-Jan.} + \beta MKT_t + \beta_{-1} MKT_{t-1} + hHML_t + mMOM_t + qQMJ_t + \epsilon_t$$

	$\alpha_{Jan.}$	$\alpha_{Non-Jan.}$	β	β_{-1}	h	m	q	R^2	Jan. diff
Full Sample	0.0115	-0.0007	-0.2112***	0.1177***	-0.1765***	-0.0516*		0.1816	0.0123**
(1986-2015)	(1.53)	(-0.33)	(-6.06)	(3.65)	(-5.56)	(-1.67)			(2.45)
	0.0104	0.0008	-0.2467***	0.1169***	-0.1665***	0.0141	-0.2539***	0.2722	0.0096*
	(1.46)	(0.35)	(-7.40)	(3.84)	(-5.54)	(0.46)	(-6.57)		(1.69)
Sub-Period 1	0.0081	-0.0007	-0.2537***	0.1006*	-0.2387***	-0.1886***		0.2449	0.0089
(1986-1999)	(0.59)	(-0.18)	(-4.34)	(1.89)	(-4.74)	(-2.88)			(0.39)
	0.0020	0.0031	-0.2855***	0.1106**	-0.1982***	-0.1123*	-0.3842***	0.4035	-0.0011
	(0.16)	(0.83)	(-5.46)	(2.33)	(-4.37)	(-1.89)	(-6.42)		(0.01)
Sub-Period 2	0.0143*	-0.0017	-0.1276***	0.1428***	-0.0762*	0.0142		0.1492	0.0159***
(2000-2015)	(1.90)	(-0.70)	(-3.11)	(4.05)	(-1.73)	(0.51)			(4.16)
	0.0149**	-0.0012	-0.1527***	0.1397***	-0.0935**	0.0357	-0.0752	0.1599	0.0161***
	(1.99)	(-0.50)	(-3.46)	(3.97)	(-2.06)	(1.14)	(-1.54)		(4.27)

*significance at the 10% level **significance at the 5% level ***significance at the 1% level

The table reports regression results for monthly SMB premia on the market factor MKT, its lagged value, the value factor HML, the momentum factor MOM and the quality factor QMJ. Two dummy variables for the months of January and non-January, respectively, separately capture alphas for January and for the remaining months of the year. The factors are constructed using all Swedish common stocks. Results are reported for the full sample period from 1986 until December 2015 as well as two sub-periods 1986-1999 and 2000-2015. T-statistics are shown in parenthesis below their corresponding coefficients.

that starting around the turn of the millennium a strong reverse size effect starts to exist in decile portfolios sorted on market value. In this section we showed that in addition, a significantly positive SMB January premium appears in the period 2000-2015.

4.2.4 Liquidity and the Size Effect

In their efforts to explain the size premium many researchers point out that liquidity plays an important role. For example, Amihud and Mendelson (1986) argue that illiquidity is a major driver of the size premium and Amihud et al. (2005) acknowledge that liquidity could contribute to resolving asset pricing puzzles such as the size effect. However, Asness et al. (2015) claim that controlling for quality reveals that the size premium is not subsumed by a liquidity premium. We analyze whether their result also holds for the Swedish market and regress *SMB* on the market, its lagged value, *HML*, *MOM* as well as three liquidity measures and finally control for quality by adding *QMJ*. Since we discovered a substantial positive SMB alpha in January, we further examine whether the January effect is related to liquidity. We follow Asness et al. (2015) and construct the following liquidity measures: the liquidity risk factor-mimicking portfolio $LIQRISK$ following Pastor and Stambaugh (2003), the short-term reversal factor $STREV$ following Kenneth French's website, which can be interpreted as a proxy for the returns from liquidity provision according to Nagel (2012), and the liquidity factor *LIQ* following Ibbotson et al. (2013) which is based on the decile spread between portfolios sorted on turnover.

Table 9 reports regression results for our full sample as well as two sub-samples that contain the months of January only and the months from February to December only, respectively. The first row shows the regression of *SMB* on the Fama and French (1993) factors including the lagged market factor and MOM resulting in a size premium close to zero, which we analyzed earlier already. Adding the liquidity factors in row two negatively affects alpha, which slightly decreases by 3 bps. This could indicate that the size premium is partially explained by an illiquidity premium. While SMB has a positive but insignificant relation to the liquidity risk factor-mimicking portfolio $LIQRISK$, it loads significantly positive on *LIQ* as per Ibbotson et al. (2013), which is consistent with intuition and literature as in Amihud (2002), Hou and Moskowitz (2005) and Asness et al. (2015). Small stocks have less turnover than big stocks and thus are less liquid leading to the positive exposure to LIQ. However, loading on $STREV$ is significantly negative, which seems puzzling as it is in contrast to findings from Asness et al. (2015). Apparently, the short term reversal strategy fares better for big stocks than for small stocks in our

Table 9: The Size Effect Controlling for Liquidiy

$$SMB_t = \alpha + \beta MKT_t + \beta_{-1} MKT_{t-1} + hHML_t + mMOM_t + l_1 LIQRISK_t + l_2 STREV_t + l_3 LIQ_t + qQMJ_t + \epsilon_t$$

	α	β	β_{-1}	h	m	l_1	l_2	l_3	q	R^2
Full Sample	0.0003	-0.2105***	0.1207***	-0.1750***	-0.0529*					0.1758
(1986-2015)	(0.11)	(-6.03)	(3.74)	(-5.50)	(-1.71)					
	0.0000	-0.1308***	0.1149***	-0.2133***	-0.0694**	0.0176	-0.0998***	0.0913***		0.2216
	(-0.01)	(-3.31)	(3.65)	(-6.53)	(-2.23)	(0.72)	(-2.75)	(3.22)		
	0.0016	-0.1715***	0.1136***	-0.2017***	-0.0025	0.0162	-0.1402***	0.0796***	-0.2752***	0.3253
	(0.80)	(-4.60)	(3.87)	(-6.62)	(-0.84)	(0.71)	(-4.09)	(3.01)	(-7.28)	
January	0.0084	-0.2778**	0.1179	-0.0241	0.2702**					0.4963
(1986-2015)	(1.21)	(-2.45)	(0.76)	(-0.21)	(2.52)					
	0.0071	-0.2719**	0.1047	0.0018	0.2771**	0.0696	-0.0587	0.0078		0.5392
	(0.86)	(-2.17)	(0.60)	(0.01)	(2.38)	(1.36)	(-0.34)	(0.09)		
	0.0093	-0.2572**	0.0709	-0.0573	0.2789**	0.0671	-0.1146	0.0375	-0.1454	0.5607
	(1.08)	(-2.03)	(0.40)	(-0.38)	(2.39)	(1.30)	(-0.63)	(0.39)	(-0.99)	
Feb.-Dec.	0.0003	-0.2111***	0.1133***	-0.1840***	-0.0757**					0.1782
(1986-2015)	(-0.15)	(-5.80)	(3.45)	(-5.61)	(-2.36)					
	-0.0011	-0.1158***	0.1099***	-0.2382***	-0.0983***	-0.0011	-0.1165***	0.1121***		0.2374
	(-0.48)	(-2.82)	(3.45)	(-7.04)	(-3.07)	(-0.04)	(-3.07)	(3.80)		
	0.0006	-0.1618***	0.1097***	-0.2122***	-0.0259	0.0013	-0.1440***	0.0894***	-0.2667***	0.3309
	(0.30)	(-4.13)	(3.67)	(-6.63)	(-0.81)	(0.05)	(-4.01)	(3.20)	(-6.64)	

*significance at the 10% level **significance at the 5% level ***significance at the 1% level

The table presents time series regressions of monthly SMB returns on the market factor MKT, its lagged value, the value factor HML, the momentum factor MOM, three proxies for liquidity and liquidity risk as well as the quality factor QMJ. The liquidity factors are the short-term reversal factor $STREV$, the decile spread in portfolios sorted on turnover LIQ and the factor-mimicking portfolio of liquidity risk $LIQRISK$. The factors are constructed using all Swedish common stocks. Results are reported for the full sample period from July 1986 to December 2015 as well as for the months of January only and for the months February-December only. T-statistics are shown in parenthesis below their corresponding coefficients.

Swedish sample.

The third row adds *QMJ* and again shows a significant negative loading of *SMB* on quality. As already seen in previous analyses, alpha substantially increases by 16 bps, which is significant from an economic perspective. Remember, that after controlling for QMJ without controlling for liquidity, we previously have seen an alpha of 16 bps as well. Hence, the size effect is not subsumed by an illiquidity premium as Asness et al. (2015) find as well. Similarly, loading on LIQ and $LIQRISK$ decline as it is partially soaked up by the presence of QMJ. Exposure to $STREV$, however, further declines after controlling for QMJ leading to a negative coefficient of -0.14.

Separately looking at the January and the February to December sample confirms the previous observations. Adding the liquidity factors to the regression substantially lowers alpha by 13 bps in January and 14 bps in the February to December sample, respectively, thus allowing for the conclusion that the size effect is partly explained by exposure to illiquidity. However, in both cases controlling for quality takes away this argument and raises alpha to 93 bps and 6 bps, respectively. Again, we see the January effect which we uncovered previously. However, several liquidity measures do not explain this anomaly even after controlling for quality. In comparison to the full sample, the January sample does not show a significant exposure to $STREV$ and LIQ anymore which is in line with Asness et al. (2015) and due to too few observations in January. The same logic explains the still negative but insignificant exposure to QMJ. For the February to December sample, we see the same patterns as for the full sample.

We have shown that controlling for quality removes what was preliminary identified as exposure of *SMB* to illiquidity. Therefore, we conclude that the size premium is not subsumed by an illiquidity premium in Sweden, which is in line with Asness et al. (2015)'s findings in the US market.

A caveat to the previous analysis is the noise in measuring liquidity. This is apparent when studying the correlation between the three liquidity factors used. All of them reflect different approaches of measuring liquidity but despite of that they are largely uncorrelated. This could indicate that the factors measure different aspects of liquidity that are not picked up by the others. In this case a composite measure as used by Asness et al. (2014) in the construction of the quality factor might improve the explanatory power of a liquidity factor. However, it certainly shows the complexity and noise in the process of measuring liquidity.

4.3 Dissection into Size and Quality/Junk

In the preceding analyses we already identified a relationship between size and quality. Forming 25 portfolios independently sorted on size and quality, we have shown that the quality-minus-junk factor and the small-minus-big factor do not measure the same effect as both QMJ and SMB are significant after controlling for size and quality, respectively. Additionally, we have shown that especially small junk stocks appear to drive both effects. Furthermore, we have also seen that controlling for quality restores a positive performance of SMB, though a statistically insignificant one. Nevertheless, the economic impact is eye-catching and persistently occurred in all our regression analyses.

To examine the interaction between size and quality in more detail, we separately investigate the six independently sorted size/quality portfolios *Small Junk*, *Big Junk*, *Small Neutral*, *Big Neutral*, *Small Quality* and *Big Quality*. Recall that QMJ is constructed as an equally-weighted average of the two quality minus the two junk portfolios excluding the two neutral portfolios. Subsequently, we regress all portfolios individually on MKT, the lagged market factor, the value factor HML, the size factor SMB, the momentum factor MOM and the quality factor QMJ. With respect to Asness et al. (2015), we include SMB and QMJ to account for any exposure to size and quality in case that the portfolios just load differently on these factors. Directly controlling for exposure to size (SMB) and quality (QMJ) enables us to concentrate on the relation between size and quality and to uncover unexplained returns.

Our analysis is divided into two parts. First, we show summary statistics of the six size/quality portfolios. Second, in a regression analysis, we explain returns of these six portfolios with common factors. Our results are shown in Table 10.

Panel A reports general characteristics of the six portfolios including average monthly returns, standard deviation and Sharpe ratios. Small quality stocks earn 0.45% on average compared to a mean return of 0.50% for big quality stocks. Hence, in the domain of quality stocks the return difference between small and big stocks is rather small. Likewise, the average return difference between small neutral and big neutral stocks is also rather small at 8 bps. Examining junk stocks, however, shows that small stocks have an average monthly value-weighted return of -0.78%, which is significant at the 10% significance level, while big junk stocks basically show no return on average. This indicates, that small junk stocks mainly drive the *reverse* size effect in Sweden and majorly contribute to the performance of QMJ. Moreover, both average returns and Sharpe ratios reveal a monotonic relationship between size and quality. For each quality section, big stocks have

Table 10: Dissection into Size and Quality/Junk

Panel A: Summary Statistics

	μ (t-statistic)	σ	Sharpe Ratio
$SmallJunk$	-0.78%* (-1.69)	8.65%	-0.0898
$BigJunk$	0.00% (0.00)	10.54%	0.0001
$SmallNeutral$	0.14% (0.37)	7.06%	0.0196
$BigNeutral$	0.22% (0.55)	7.45%	0.0293
$SmallQuality$	0.45% (1.35)	6.30%	0.0717
$BigQuality$	0.50% (1.40)	6.68%	0.0745

Panel B: 2x3 Size-Quality Sort Portfolio Regressions

$$= \alpha + \beta MKT_t + \beta_{-1} MKT_{t-1} + sSMB_t + hHML_t + mMOM_t + qQMJ_t + \epsilon_t$$

	α	β	β_{-1}	s	h	m	q	R^2
$SmallJunk_t$	-0.0070***	1.0293***	0.0225	0.6764***	0.0432	0.0477*	-0.4070***	0.8356
	(-3.58)	(30.86)	(0.78)	(13.58)	(1.48)	(1.66)	(-10.68)	
$BigJunk_t$	0.0074***	0.8082***	-0.0346	-0.2317***	-0.0535	-0.0424	-1.0592***	0.8260
	(3.05)	(19.34)	(-0.96)	(-3.71)	(-1.47)	(-1.18)	(-22.19)	
$SmallNeutral_t$	-0.0006	0.8832***	0.0333	0.4943***	0.1383***	0.0165	-0.0906**	0.7286
	(-0.32)	(25.26)	(1.10)	(9.46)	(4.53)	(0.55)	(-2.27)	
$BigNeutral_t$	-0.0015	1.0557***	0.0444***	-0.0497**	0.0332**	-0.0087	0.0407**	0.9450
	(-1.53)	(63.62)	(3.09)	(-2.00)	(2.29)	(-0.61)	(2.15)	
$SmallQuality_t$	0.0004	0.9068***	0.0820***	0.4515***	0.0301	0.0224	0.1811***	0.8159
	(0.29)	(35.32)	(3.69)	(11.77)	(1.34)	(1.01)	(6.17)	
$BigQuality_t$	0.0000	0.9307***	-0.0941***	-0.0068	-0.0404*	-0.0171	0.3527***	0.8123
	(0.01)	(33.85)	(-3.96)	(-0.16)	(-1.68)	(-0.72)	(11.23)	

*significance at the 10% level **significance at the 5% level ***significance at the 1% level

The table covers six portfolios constructed from independent size and quality sorts using all Swedish common stocks. The two quality and the two junk portfolios are used to build the QMJ factor. Panel A presents monthly summary statistics for the six portfolios. The average value-weighted return (μ) and its t-statistic, standard deviation (σ) and the resulting Sharpe ratio are shown. Panel B reports regression results for monthly returns of each of the six portfolios on the market factor MKT, its lagged value, the size factor SMB, the value factor HML, the momentum factor MOM and the quality factor QMJ. T-statistics are shown in parenthesis below their corresponding coefficients.

higher returns and Sharpe ratios than small stocks again indicating the aforementioned *reverse* size effect. Moreover, high quality stocks have higher average returns, lower standard deviations and higher Sharpe ratios than low quality or junk stocks.

Panel B displays regression results. All six portfolios load significantly positive on the market, which is not surprising. Interestingly, exposure to the lagged market factor is only significant for the quality portfolios and *Big Neutral*, which tends to be of higher quality compared to its smaller counterpart. Probably most striking, *Small Junk* and *Big Junk* show significant abnormal returns even after controlling for size and quality. *Small Junk* shows a significant negative alpha of -0.70% and thus, the factors included in the regression do not fully explain the substantial negative performance of small junk stocks. The coefficient on SMB is significantly positive and amounts to 0.68 and loading on QMJ is significantly negative with a coefficient of -0.41. This is not surprising as the considered stocks are characterized as small and junky. Remember, that we included both QMJ and SMB in the regression to eliminate any exposure to size and quality. Interestingly, the heavy loading on junk can only mitigate the poor performance of *Small Junk*, which is raised by 8 bps compared to its average return, but a massive -70 bps is left unexplained.

Big Junk has a significant alpha amounting to 0.74%. Loadings on both SMB and QMJ are significantly negative, which is not staggering again as *Big Junk* consists of big and junk stocks. However, *Big Junk* loads more extremely negative on QMJ than *Small Junk* with a coefficient of -1.06. Even though we have seen in Panel A, that *Big Junk* has basically no average return, controlling for several factors and most importantly quality, uncovers a substantial abnormal return, which is not explained by the model. Hence, the aforementioned different average returns between *Small Junk* and *Big Junk* are even emphasized after controlling for quality. In line with previous results for SMB, controlling for liquidity does not subsume these unexplained returns (see Appendix A5). Basically, there is no improvement in precision measured by R-square and unexplained returns for *Small Junk* and *Big Junk* are mitigated but still statistically significant.

Looking at the two neutral portfolios, alphas of both *Small Neutral* and *Big Neutral* are slightly negative and insignificant, thus there is no abnormal return that is not explained by the six factor model including size and quality. *Small Neutral* has a significant positive exposure to SMB and a significant negative exposure to QMJ. Hence, the portfolio comprises small stocks that belong more to junk stocks than to quality stocks. Contrary, *Big Neutral* has a significantly negative loading on SMB and a significantly positive loading on QMJ leading to the conclusion that *Big Neutral* consists of big stocks that are of rather high quality than low quality.

Regression coefficients for *Small Quality* and *Big Quality* show similar patterns. Alphas of both *Small Quality* and *Big Quality* are very small and insignificant. Both factors load extremely positive and statistically significant on QMJ, thus eliminating exposure to quality, which primarily explains insignificant alphas of nearly zero. *Small Quality* also loads positively on SMB which is in line with expectations, since *Small Quality* comprises small and high quality stocks. Similarly, *Big Quality* loads, though statistically insignificant, slightly negative on SMB. This shows that big quality stocks tend to be rather not small, though a stronger negative loading on size might have been expected. However, when analyzing the relation between size and value, Fama and French (1996) also find that the loading of big stocks on SMB is only marginally negative and statistically insignificant for big value stocks. In conclusion, *Big Quality* and *Small Quality* do not show additional returns that are not explained by the six factors including size and quality.

In order to shed even more light on which subsets of stocks pose the greatest challenges to current asset pricing models, we look at time series regressions of size and quality decile portfolios as well as 25 portfolios formed on size and quality. Results are similar as before and reported in the appendices. Regression results for size decile portfolios (see Appendix A6) show an increasing pattern of R-square values. Generally, decile portfolios with larger stocks in terms of market value are far better explained by our model and the R-square of the largest decile even amounts to 97%. In contrast, the smallest two decile portfolios are poorly explained with R-square values of 28% and 34%, respectively. Consequently, alphas are largest in absolute terms and highly significant. Interestingly, the smallest size decile portfolio features a positive loading on quality. This could indicate that the smallest of the small stocks in our sample might not be that junky after all - as measured by QMJ. However, the extremely low precision in the explanation of the smallest stocks certainly illustrates that some aspects of the behavior of returns of small stocks is not captured by our factors. Regression results for quality decile portfolios (see Appendix A7) also show the lowest precision for the lowest quality portfolio. This portfolio shows a strong positive loading on size meaning that the junkiest stocks tend to be rather small.

Regression results for the 25 portfolios formed on size and quality (see Appendix A8) show significant alphas for the the smallest and junkiest portfolios supporting the finding that this section is troublesome for our factor model. Interestingly, loadings on quality are significant for portfolios of bigger stocks but never significant for the smallest portfolios. The bottom line again is that return behavior of the smallest and junkiest stocks is relatively poorly explained whereas the model works well for rather large and high quality stocks as inferred from R-square values.

Concluding, returns of high quality and large stocks are fairly well explained by a set of factors comprising MKT, its lagged value, HML, SMB, MOM and QMJ. In fact it is the most extreme stocks in terms of small size and junk that pose the biggest challenge to our asset pricing model. In the realm of junk stocks we uncovered a substantial difference between small and big stocks, which is puzzling and not explained by loading on size or quality. Apparently, another effect among junk stocks exists which is linked to size and which is not explained through our asset pricing model. Furthermore, we showed that these alphas primarily drive the reverse size effect and in addition, explain the outperformance of a quality strategy among small stocks versus big stocks.

5 Robustness Tests

5.1 Results for the Nordics

After a thorough analysis of the Swedish market we are interested if the identified patterns hold in the smaller Nordic countries Norway, Denmark and Finland as well as in the combined Nordic region as a whole.

SMB. Size premia are all negative and amount to -2.18% p.a. for Sweden, -0.27% p.a. for Norway, -2.47% p.a. for Denmark, -1.92% p.a. for Finland and -4.23% for the whole Nordic market (see Appendix A9). Most interestingly, the average size premium for the Nordics is the largest in absolute terms and is the only one showing statistical significance. Hence, in contrast to Annaert et al. (2002), we do not find evidence that investigating a broader region reveals a positive size effect. Instead, the whole Nordic region behaves similar to the Swedish market as well as the other Nordic countries and big stocks outperform small stocks to an even greater extent than on a country-by-country basis. Hence, we observe an even higher negative size premium or *reverse* size effect.

Other Factors. Comparing individual Nordic countries and the whole Nordic region, the value factor HML behaves similar to the size premium. While HML is insignificant for the four countries individually, combining all stocks into one Nordic dataset emphasizes the value effect and reveals a significant value premium of 7.52% p.a. The momentum factor MOM shows similar results as our previous analyses on the Swedish market. Characteristic for the MOM factor are high average monthly returns and Sharpe ratios for the Nordic countries Sweden, Norway, Denmark and Finland and the whole Nordic region. As seen for the Swedish market, QMJ works fairly well for the Nordic region and most of the individual countries with the exception of Finland.

SMB Controlling for Quality. Figure 9 reports changes in *SMB* alpha for each Nordic country and the Nordic region from regressing SMB on the respective market factor, its lagged value, *HML*, *MOM* and additionally controlling for the quality factor QMJ versus the same regression without QMJ. In every national market as well as the Nordic region controlling for quality raises alpha and *SMB* loads significantly negative on quality, which makes our results very consistent. For the Nordic region, this increase in alpha is even high enough to dismantle the significant negative size premium emphasizing the positive impact of the quality factor on the size effect. Detailed results of these regressions are reported in Appendix A10.

Figure 9: SMB Alpha Improvement after Controlling for Quality

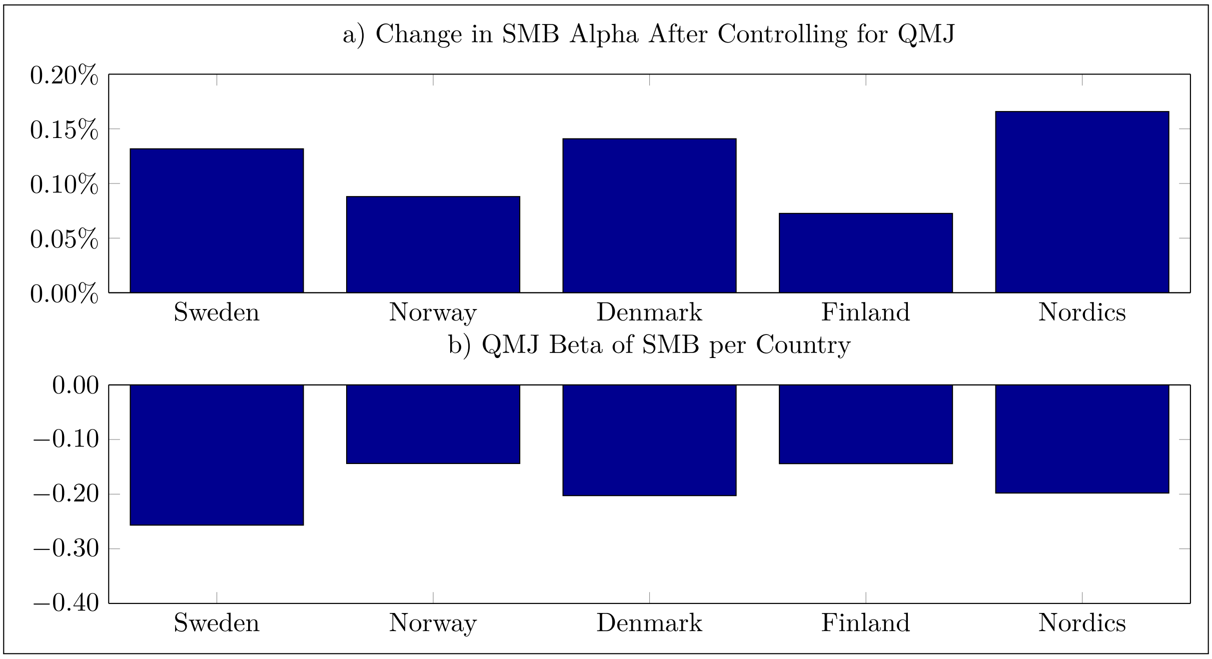


Chart a) plots the change in SMB alpha after controlling for QMJ compared to regressing the size premium on the market factor MKT, its lagged value, the value factor HML and the momentum factor MOM. Chart b) shows the loading of SMB on the quality factor QMJ. Regressions are performed for the full sample period per country or region.

January effect. Chart a) of Appendix A11 displays average monthly returns for January as well as January alphas of SMB regressed on a January and non-January dummy variable, the market factor, its lagged value, HML, MOM and QMJ for the individual Nordic countries Sweden, Norway, Denmark and Finland and the whole Nordic region. With the exception of Denmark, small stocks outperform big stocks in January. After controlling for the aforementioned factors, an even stronger outperformance of small stocks against big stocks is observable. Denmark now shows a positive SMB return as well. Chart b) illustrates average monthly returns for the months February-December as well as non-January alphas of the regression described above. Again, results are very consistent among the different countries. SMB returns for non-January months are basically zero or slightly negative leading to the conclusion that even after controlling for quality, a strong January effect still exists.

Dissection into Size and Quality. Reexamining the previously found evidence that a six-factor model including the market factor, its lagged value, the size factor SMB, the value factor HML, the momentum factor MOM and the quality factor QMJ cannot fully explain returns of small junk and big junk stocks for the Swedish market, we find similar results for the Nordic region and most of the individual Nordic countries Norway, Denmark and Finland (see Appendices A12, A13, A14, A15). While Norway shows only significantly negative abnormal returns for small junk stocks, the Nordic region and Denmark show significant alphas for both small junk stocks and big junk stocks. However, trends are similar for all countries and the Nordics. There is a negative alpha for small junk stocks and a positive alpha for big junk stocks. This is also true for the smaller Finnish sample, however, we do not observe significant results, which might be caused by limited data. Loading on the quality factor is consistent and significant for all datasets. Junk stocks always load significantly negative on QMJ and quality stocks always load significantly positive on QMJ regardless of the investigated region.

5.2 Breakpoints and Sorting Methods

We test our results from the Swedish sample for robustness by applying different breakpoints and sort mechanisms. As discussed earlier these specific methodological aspects present particular challenges and are approached very differently by academic research. First, we implement the 80th percentile of the total number of companies as size breakpoint as done by Asness et al. (2015). Afterwards, we use conditional sorts instead of independent sorts similar to Asness et al. (2014) when first introducing the QMJ factor.

80th percentile. Regression results for SMB on our set of factors provide two main takeaways (see Appendix A16). First, controlling for quality positively impacts alpha, although the effect is far less strong in comparison to our results based on factors constructed applying the 12.5th percentile market value size breakpoint. This is likely related to the second observation, which is a very significant negative size premium that is far lower than seen before. The reason for this lies in a lower number of stocks included in the small portfolio as the 80th percentile fails to accurately proxy the NYSE median market capitalization for the better part of our sample period. In terms of aggregate market value on average only 6.5% are included in the small portfolio since 1995. Hence, the *reverse* size premium is emphasized as returns of smaller stocks are relatively lower. Generally, precision is fairly low and loading on QMJ is not significant as the portfolio construction is more influenced by the smaller section of stocks that provides challenges to the model.

Conditional sort. Regression results for SMB on various factors (see Appendix A17) again show that controlling for QMJ heavily increases alpha compared to only controlling for the Fama and French (1993) factors including the lagged market value and MOM. In contrast to our base case, alphas remain negative after controlling for quality but are not reliably different from zero. The largest downside of a conditional sort mechanism is that always exactly the same percentage of stocks in the big and small portfolios are classified as quality/junk even though an independent sort might not identify any quality/junk stock in a given month. Likely, a sufficient sample size is required that antagonizes the drawback of the sort methodology, which is usually provided in studies covering the US market. However, it is questionable whether our sample size is big enough to do so. In any case, this analysis supports the evidence of a non-significant SMB return as well as the positive impact of controlling for quality.

6 Conclusion and Further Remarks

Generally, we discover an overperformance of big stocks versus small stocks in Sweden and the Nordics leading to a *reverse* size effect. Emphasizing this finding, returns of size decile portfolios almost monotonically increase with market values. Hence, extremes matter as focusing only on the smallest and biggest stocks reveals an even greater negative size effect. Besides, we find evidence for the existence of a January effect. While SMB returns are remarkable and positive in January, the small-minus-big strategy yields low and negative returns for the remaining months.

Further we find that the positive impact of controlling for quality on SMB premia is strikingly persistent among all Nordic countries and the whole Nordic region, illustrating the importance of the quality factor on the size effect. The SMB factor, and hence small stocks, features a high exposure to junk which is at least partially removed by a significant negative loading on QMJ. Thus, the size premium increases and the performance of basic SMB compared to a hedged SMB strategy, which hedges for exposure to other factors including QMJ, is economically considerable. Moreover, we find that the size effect is not subsumed by current state-of-the-art liquidity measures.

We further find that small stocks as well as junk stocks pose major challenges for current asset pricing models. Decile portfolios containing the smallest stocks in terms of market values, decile portfolios comprising the lowest quality or junky stocks and the two junk portfolios used in the formation of the QMJ factor are all but well explained by a six factor model including the market factor, its lagged value, the value factor, the size factor, the momentum factor and the quality factor, leaving substantial abnormal returns. For the Swedish and Nordic market, the finding of a significant negative alpha for the small junk portfolio juxtaposed by a significant positive alpha for the big junk portfolio is striking. All of the previous provide strong indications that small and especially junk stocks feature certain characteristics that are not captured by the six factor model.

In addition, these findings challenge risk-based explanations of the size premium, which would require small and junk stocks to provide an additional return in compensation for their relatively higher risk. However, after controlling for exposure to junk, the size effect is less long smaller junk stocks and thus also less long more illiquid stocks but performance increases substantially in economic terms.

Subsequent empirical studies may consider why a *reverse* size effect exists in the Nordics and whether this phenomenon occurs in other European countries as well. However, a crucial topic for asset pricing theory will be to further investigate the relation between size and quality, especially focusing on junk stocks. It appears that risk-based theories and rational models face great challenges.

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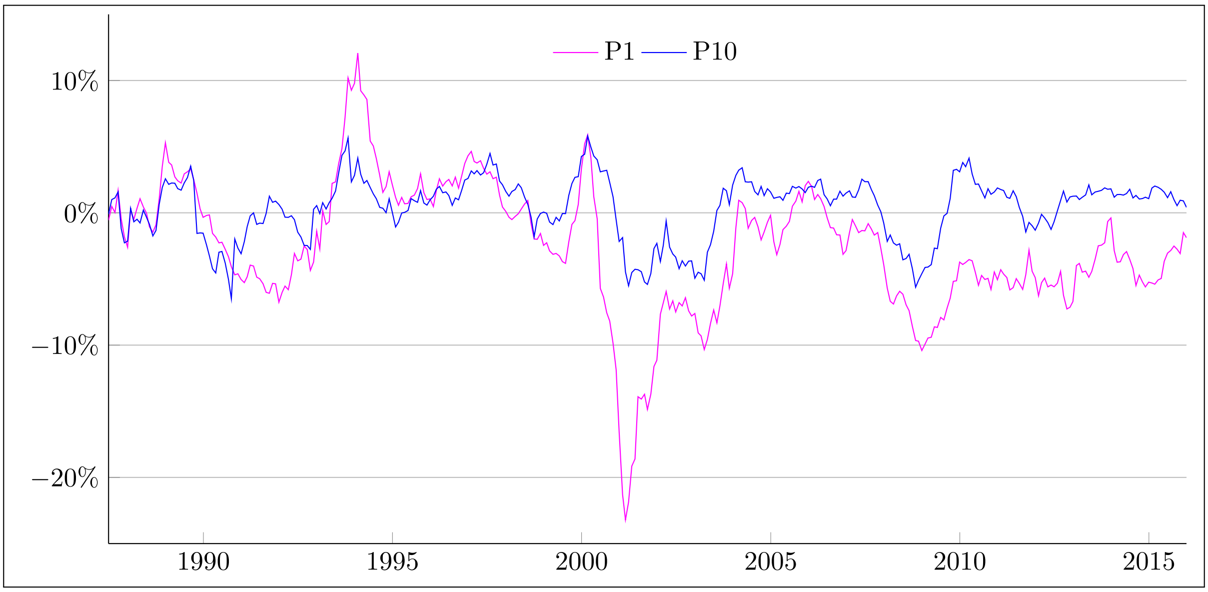
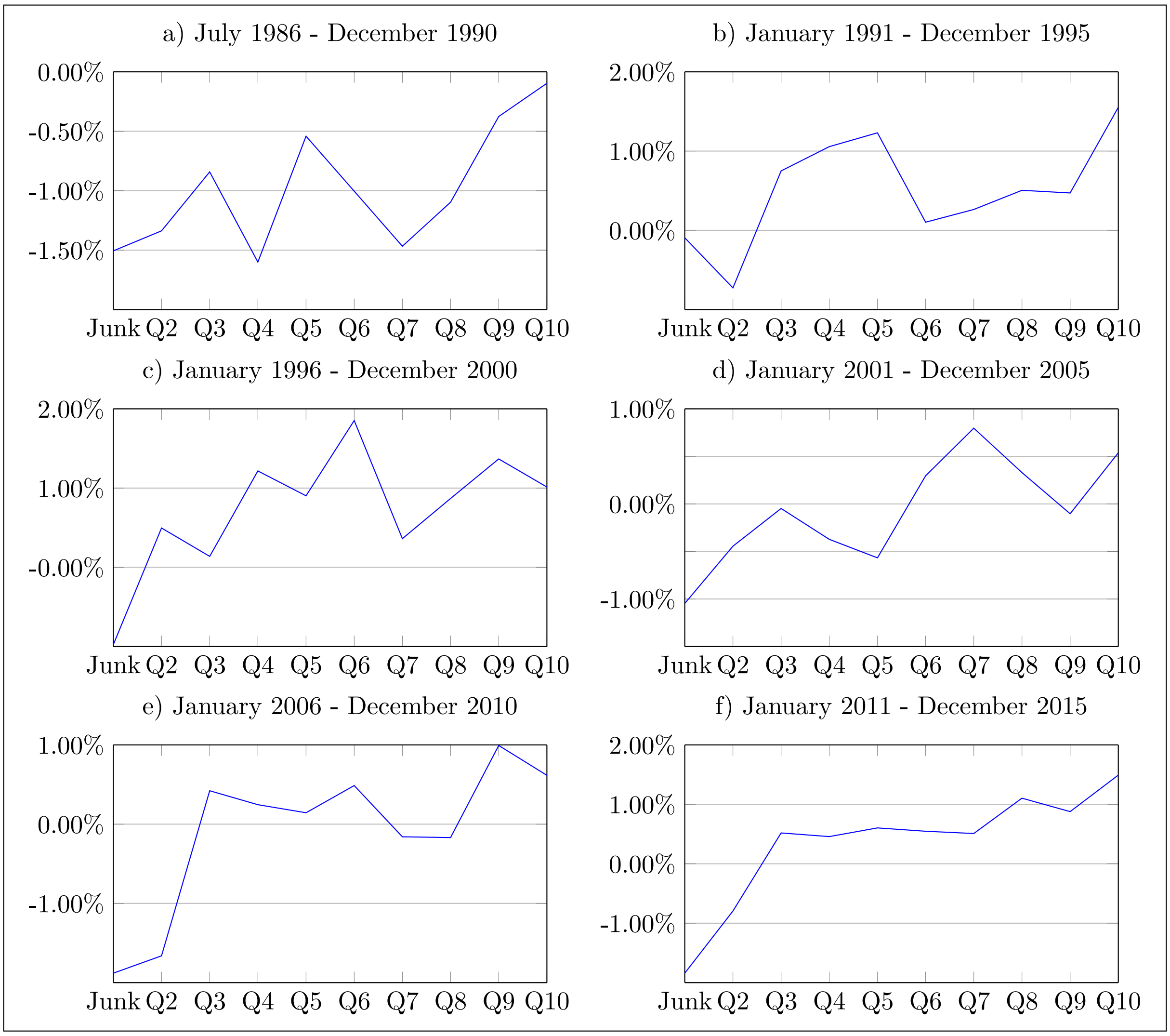
Appendices

Appendix A1: Rolling 1-Year Value-Weighted Mean Returns of the Smallest and Largest Size Decile Portfolios



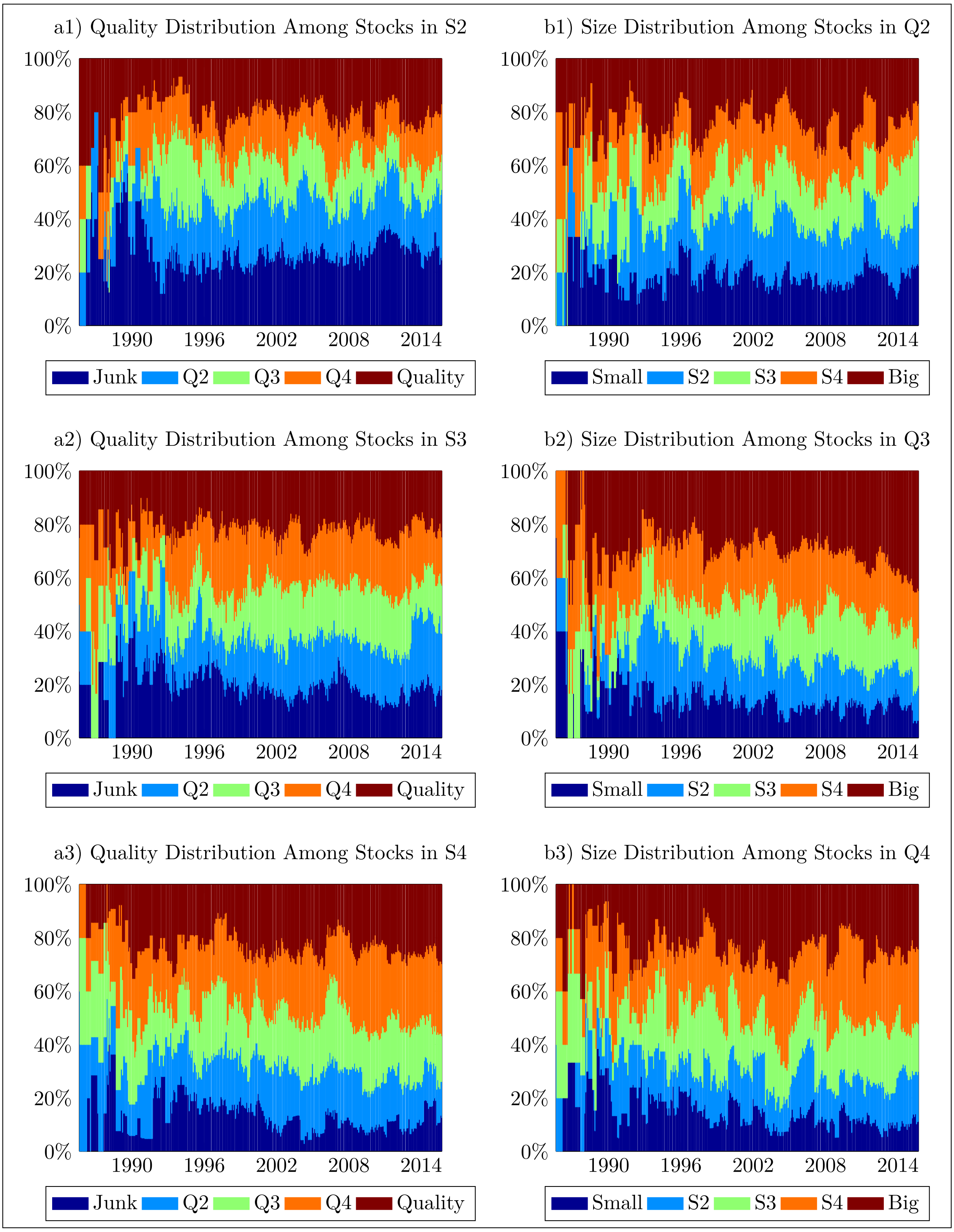
The Figure plots rolling 1-year value-weighted average returns of size decile portfolios obtained from sorting all Swedish common stocks on market capitalization every June. P1 contains the 10% of stocks with the smallest market values and P10 the 10% of stocks with the largest market values. Returns are shown every month from June 1987 to December 2015 as 12 months of return data is required to compute the rolling returns.

Appendix A2: Mean Value-Weighted Quality Decile Returns for Five-Year Periods



This figure plots average value-weighted returns for 10 quality decile portfolios obtained from monthly sorts of Swedish common stocks on quality scores following Asness et al. (2014). P1 contains the 10% of stocks with the lowest quality scores and P10 the highest 10%. Chart a) shows mean returns for the period from July 1986 until December 1990 and charts b) to f) present mean returns for consecutive five-year periods until December 2015.

Appendix A3: Size and Quality Distribution Among Stocks in the Middle Three Size and Quality Quintile Portfolios



The Figure shows the size and quality distribution among Swedish common stocks within quintile portfolios obtained from two independent sorts on market capitalization and quality score, respectively. Each sort divides the universe of stocks in quintile portfolios containing 20% of the total number of stocks. Charts a1), a2) and a3) portray the quality distribution in the three middle size quintiles (S2, S3 and S4). Charts b1), b2) and b3) depict the size distribution in the middle three quality quintiles (Q2, Q3 and Q4).

Appendix A4: Correlation of Monthly Quality Factor Returns

	QMJ	Profitability	Growth	Safety	Payout
QMJ	1.00				
Profitability	0.62	1.00			
Growth	0.42	0.54	1.00		
Safety	0.64	0.37	0.16	1.00	
Payout	0.50	0.28	-0.01	0.19	1.00

The table reports linear correlation coefficients of monthly returns of the quality-minus-junk (QMJ) factor and the four quality factors $Profitability$, $Growth$, $Safety$ and *Payout* following Asness et al. (2014). The factors are constructed using all Swedish common stocks.

Appendix A5: Dissection into Size and Quality/Junk: Controlling for Liquidity

$$= \alpha + \beta MKT_t + \beta_{-1} MKT_{t-1} + sSMB_t + hHML_t + mMOM_t + +qQMJ_t + l_1 LIQRISK + l_2 STREV + l_3 LIQ + \epsilon_t$$

	α	β	β_{-1}	s	h	m	q	l_1	l_2	l_3	R^2
$SmallJunk_t$	-0.0066***	1.0069***	0.0215	0.6876***	0.0585*	0.0554*	-0.4060***	0.0190	0.0047	-0.0369	0.8369
	(-3.37)	(27.21)	(0.74)	(13.25)	(1.88)	(1.89)	(-10.37)	(0.87)	(0.14)	(-1.43)	
$BigJunk_t$	0.0061**	0.8434***	-0.0376	-0.2035***	-0.0644*	-0.0442	-1.0231***	-0.0313	0.1365***	0.0682**	0.8340
	(2.52)	(18.56)	(-1.06)	(-3.19)	(-1.68)	(-1.23)	(-21.28)	(-1.17)	(3.29)	(2.15)	
$SmallNeutral_t$	-0.0018	0.9660***	0.0344	0.4531***	0.0840***	-0.0011	-0.0908**	-0.0266	0.0023	0.1354***	0.7486
	(-0.90)	(25.78)	(1.17)	(8.62)	(2.66)	(-0.04)	(-2.29)	(-1.20)	(0.07)	(5.17)	
$BigNeutral_t$	-0.0014	1.0454***	0.0438***	-0.0427*	0.0408***	-0.0051	0.0426**	0.0074	0.0073	-0.0166	0.9454
	(-1.39)	(56.74)	(3.04)	(-1.65)	(2.63)	(-0.35)	(2.18)	(0.68)	(0.44)	(-1.29)	
$SmallQuality_t$	0.0000	0.9082*	0.0806***	0.4725***	0.0348	0.0241	0.1980***	-0.0128	0.0630**	0.0074	0.8194
	(0.01)	(-1.68)	(3.64)	(11.89)	(1.46)	(1.07)	(6.61)	(-0.77)	(2.44)	(0.38)	
$BigQuality_t$	-0.0005	0.9421	-0.0967***	0.0117	-0.0407	-0.0130	0.3730***	0.0005	0.0782***	0.0239	0.8171
	(-0.34)	(-1.23)	(-4.09)	(0.27)	(-1.60)	(-0.54)	(11.67)	(0.03)	(2.83)	(1.13)	

*significance at the 10% level **significance at the 5% level ***significance at the 1% level

The table covers six portfolios constructed from independent size and quality sorts using all Swedish common stocks. The two quality and the two junk portfolios are used to build the QMJ factor. The table reports regression results for each of the six portfolios on the market factor MKT, its lagged value, the size factor SMB, the value factor HML, the momentum factor MOM, the quality factor QMJ and the three liquidity measures $LIQRISK$, $STREV$ and LIQ. T-statistics are shown in parenthesis below their corresponding coefficients.

Appendix A6: Time Series Regressions for Monthly Excess Returns of Size Decile Portfolios

$$P_t = \alpha + \beta MKT_t + \beta_{-1} MKT_{t-1} + sSMB_t + hHML_t + mMOM_t + qQMJ_t + \epsilon_t$$

	Small	P2	P3	P4	P5	P6	P7	P8	P9	Big
α	-0.0313***	-0.0179***	-0.0148***	-0.0098**	-0.0046**	-0.0031	-0.0043**	-0.0038**	0.0023	0.0002
	(-6.03)	(-4.41)	(-5.27)	(-2.53)	(-1.96)	(-1.47)	(-2.30)	(-2.04)	(1.36)	(0.32)
	GRS F-statistic=5.17	p(GRS) =0.0000								
β	0.8302***	0.7649***	0.8094***	0.9965***	0.8693***	0.9097***	0.9946***	1.0940***	0.9231***	1.0129***
	(9.35)	(10.97)	(16.84)	(14.97)	(21.70)	(25.09)	(31.14)	(34.68)	(32.16)	(91.69)
β_{-1}	0.3168***	0.2158***	0.0997**	0.1239**	0.0359	0.0453	0.0563**	0.0811***	0.0343	-0.0117
	(4.12)	(3.58)	(2.40)	(2.15)	(1.04)	(1.44)	(2.04)	(2.97)	(1.38)	(-1.22)
s	0.5365***	0.4776***	0.5249***	0.7120***	0.6317***	0.4746***	0.4570***	0.6401***	0.2804***	-0.1801***
	(4.04)	(4.59)	(7.31)	(7.16)	(10.56)	(8.76)	(9.58)	(13.58)	(6.54)	(-10.91)
h	0.0304	0.0301	-0.0346	0.1752***	0.0415	0.0836***	0.0032	0.3136***	0.0728***	-0.0338***
	(0.39)	(0.49)	(-0.82)	(3.01)	(1.19)	(2.64)	(0.11)	(11.38)	(2.91)	(-3.51)
m	0.0678	0.0094	0.0415	0.1848***	-0.0431	-0.0221	-0.0212	-0.0854***	0.0089	-0.0121
	(0.89)	(0.16)	(1.01)	(3.23)	(-1.25)	(-0.71)	(-0.77)	(-3.15)	(0.36)	(-1.27)
q	0.1964*	0.0928	-0.0118	-0.1550**	-0.1174**	0.0901**	0.0022	0.1637***	-0.0635*	0.0502***
	(1.94)	(1.17)	(-0.22)	(-2.04)	(-2.57)	(2.17)	(0.06)	(4.54)	(-1.94)	(3.98)
R^2	0.2814	0.3444	0.5389	0.4875	0.6892	0.7048	0.7956	0.8336	0.8086	0.9737

The table reports regression results of 10 size decile portfolios on the market factor MKT, its lagged value, the size factor SMB, the value factor HML, the momentum factor MOM and the quality factor QMJ. Decile portfolios are constructed sorting the whole sample of Swedish stocks on market capitalization every June and allocating 10% of the total number of stocks to each portfolio. The factors are constructed in the Swedish market as well. The GRS F-statistics of Gibbons et al. (1989) tests the hypothesis that all 10 alphas are equal to zero. p(GRS) is the p-value of the GRS F-statistic. T-statistics are shown in parenthesis below their corresponding coefficients.

Appendix A7: Time Series Regressions for Monthly Excess Returns of Quality Decile Portfolios

$$Q_t = \alpha + \beta MKT_t + \beta_{-1} MKT_{t-1} + sSMB_t + hHML_t + mMOM_t + qQMJ_t + \epsilon_t$$

	Junk	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Quality
α	-0.0126***	-0.0045	0.0077***	-0.0004	0.0015	0.0007	-0.0044*	-0.0012	0.0008	0.0044*
	(-3.52)	(-1.64)	(-3.20)	(-0.21)	(0.65)	(0.34)	(-1.90)	(-0.52)	(0.34)	(1.91)
					GRS F-statistic=2.88	p(GRS) =0.0018				
β	0.9419***	0.9081***	0.9560***	1.0419***	0.9445***	0.9179***	1.0091***	0.9463***	0.9557***	0.8688***
	(15.34)	(19.22)	(23.27)	(29.05)	(24.10)	(25.73)	(25.45)	(24.08)	(25.31)	(22.10)
β_{-1}	-0.0161	0.0629	-0.0494	0.1034***	0.0363	0.0120	0.0195	-0.0125	-0.0090	-0.1338***
	(-0.30)	(1.54)	(-1.39)	(3.33)	(1.07)	(0.39)	(0.57)	(-0.37)	(-0.27)	(-3.93)
s	0.5527***	0.0492	-0.0686	-0.1344**	0.1019*	0.1419***	0.0627	0.2242***	0.1616***	0.0470
	(6.02)	(0.70)	(-1.12)	(-2.51)	(1.74)	(2.66)	(1.06)	(3.82)	(2.86)	(0.80)
h	-0.0218	0.1671***	-0.0686*	0.0511	0.0074	0.1020***	0.2162***	0.1444***	-0.0245	-0.1367***
	(-0.41)	(4.05)	(-1.91)	(1.63)	(0.22)	(3.27)	(6.24)	(4.21)	(-0.74)	(-3.98)
m	0.1328**	-0.0879**	-0.0657*	0.0091	-0.0835**	0.0256	-0.0369	-0.0623*	0.0246	-0.0103
	(2.51)	(-2.16)	(-1.86)	(0.29)	(-2.47)	(0.83)	(-1.08)	(-1.84)	(0.76)	(-0.30)
q	-0.3418***	-0.6152***	-0.8484***	-0.1821***	0.0134	-0.0081	0.1783***	0.2003***	0.2511***	0.3795***
	(-4.87)	(-11.40)	(-18.08)	(-4.44)	(0.30)	(-0.20)	(3.94)	(4.46)	(5.82)	(8.45)
R^2	0.5269	0.7432	0.8278	0.8069	0.7181	0.7240	0.7294	0.6898	0.6909	0.6459

The table reports regression results of 10 quality decile portfolios on the market factor MKT, its lagged value, the size factor SMB, the value factor HML, the momentum factor MOM and the quality factor QMJ. Decile portfolios are constructed by monthly sorts of all Swedish stocks on quality scores following Asness et al. (2014) and allocating 10% of the total number of stocks to each portfolio. The factors are constructed in the Swedish market as well. The GRS F-statistics of Gibbons et al. (1989) tests the hypothesis that all 10 alphas are equal to zero. p(GRS) is the p-value of the GRS F-statistic. T-statistics are shown in parenthesis below their corresponding coefficients.

Appendix A8: Time Series Regressions for Monthly Excess Returns on 25 Portfolios Formed on Size and Quality

$$SQ_t = \alpha + \beta MKT_t + \beta_{-1} MKT_{t-1} + sSMB_t + hHML_t + mMOM_t + qQMJ_t + \epsilon_t$$

	Small	S2	S3	S4	Big
			α		
Junk	-0.0347***	-0.0218***	-0.0183***	-0.0094***	0.0020
	(-6.44)	(-4.03)	(-4.83)	(-2.69)	(0.53)
Q2	-0.0084*	-0.0114***	-0.0047	-0.0047	0.0020
	(-1.76)	(-2.84)	(-1.41)	(-1.43)	(1.09)
Q3	-0.0162***	-0.0074	-0.0033	-0.0031	0.0017
	(-3.36)	(-1.51)	(-0.84)	(-1.19)	(0.98)
Q4	-0.0141***	-0.0020	0.0022	0.0012	-0.0020
	(-3.03)	(-0.52)	(0.77)	(0.53)	(-0.78)
Quality	-0.0150***	-0.0104**	-0.0020	0.0041	0.0022
	(-3.10)	(-2.53)	(-0.74)	(1.61)	(1.18)
			β		
Junk	0.8216***	0.9176***	0.9940***	0.9648***	0.9946***
	(9.01)	(9.92)	(14.86)	(16.05)	(13.78)
Q2	0.6323***	0.7753***	0.8074***	1.0901***	1.0453***
	(7.69)	(11.25)	(13.70)	(19.39)	(33.11)
Q3	0.6401***	0.7189***	0.8611***	0.9912***	0.9905***
	(7.49)	(8.41)	(12.55)	(22.27)	(32.34)
Q4	0.7516***	0.7963***	0.7863***	0.9970***	0.9953***
	(9.51)	(11.32)	(16.30)	(25.24)	(22.91)
Quality	0.7564***	0.9089***	1.0115***	0.9916***	0.8706***
	(9.16)	(12.91)	(22.13)	(22.91)	(27.11)
			β_{-1}		
Junk	0.3290***	0.0896	0.1124**	0.0251	0.0606
	(3.95)	(1.13)	(1.97)	(0.48)	(0.97)
Q2	0.1449**	0.1277**	0.0161	0.0182	0.0430
	(2.03)	(2.13)	(0.32)	(0.37)	(1.57)
Q3	0.1453**	0.1199	0.0700	0.0878**	0.0266
	(2.00)	(1.64)	(1.20)	(2.28)	(1.00)
Q4	0.1865***	0.1949***	0.0561	0.0648*	-0.0175
	(2.74)	(3.31)	(1.34)	(1.90)	(-0.45)
Quality	0.2953***	0.1817***	0.0806**	0.1261***	-0.1019***
	(4.13)	(2.98)	(2.04)	(3.39)	(-3.66)
			s		
Junk	0.4673***	0.9049***	0.4246***	0.5088***	0.1374
	(3.30)	(6.60)	(4.35)	(5.74)	(1.22)
Q2	0.6414***	0.5150***	0.6858***	0.3167***	-0.1811***
	(5.31)	(4.95)	(7.94)	(3.77)	(-3.84)
Q3	0.4829***	0.5397***	0.5744***	0.5098***	0.0968**
	(3.85)	(4.32)	(5.77)	(7.67)	(2.15)
Q4	0.2434**	0.4484***	0.4633***	0.2838***	-0.0645
	(2.08)	(4.49)	(6.43)	(4.81)	(-0.99)
Quality	0.3159**	0.3312***	0.5600***	0.5560***	-0.0517
	(2.56)	(3.15)	(8.20)	(8.67)	(-1.08)

continued on next page

Appendix A8: (continued)

	Small	S2	S3	S4	Big
			h		
Junk	-0.0280	0.0725	-0.0127	-0.1682***	0.4206***
	(-0.35)	(0.90)	(-0.23)	(-3.23)	(5.58)
Q2	0.1270*	-0.0789	0.0991**	0.0914*	0.0194
	(1.78)	(-1.33)	(2.01)	(1.86)	(0.71)
Q3	0.0452	0.0706	0.0785	0.0708*	-0.0044
	(0.63)	(0.98)	(1.33)	(1.82)	(-0.16)
Q4	0.0750	0.0718	0.0425	0.1966***	0.2137***
	(1.08)	(1.22)	(1.01)	(5.70)	(5.64)
Quality	0.0271	0.1506**	0.0307	-0.0648*	-0.0925***
	(0.38)	(2.45)	(0.77)	(-1.71)	(-3.30)
			m		
Junk	-0.0916	-0.0496	-0.0976*	-0.0938*	-0.0488
	(-1.15)	(-0.63)	(-1.78)	(-1.83)	(-0.87)
Q2	-0.0499	-0.1165**	-0.0523	-0.1021**	0.0393
	(-0.72)	(-1.98)	(-1.08)	(-2.11)	(1.45)
Q3	-0.0219	-0.0906	-0.0124	0.0099	-0.0312
	(-0.31)	(-1.29)	(-0.22)	(0.26)	(-1.20)
Q4	0.0632	-0.0236	-0.1129***	-0.0884***	-0.0669*
	(0.94)	(-0.42)	(-2.72)	(-2.60)	(-1.79)
Quality	0.1288*	-0.0121	-0.0488	0.0639*	-0.0207
	(1.81)	(-0.20)	(-1.24)	(1.73)	(-0.75)
			q		
Junk	0.0935	-0.3808***	-0.1100	-0.2623***	-0.5179***
	(0.87)	(-3.63)	(-1.50)	(-3.86)	(-6.47)
Q2	-0.0291	-0.1289	-0.1276**	-0.2194***	-0.4232***
	(-0.31)	(-1.64)	(-1.97)	(-3.42)	(-11.73)
Q3	-0.0271	0.1273	-0.1537**	0.0339	0.0301
	(-0.29)	(1.36)	(-2.01)	(0.67)	(0.88)
Q4	-0.0088	0.1248*	0.1330**	0.1421***	0.2114***
	(-0.10)	(1.66)	(2.41)	(3.15)	(4.26)
Quality	0.1326	0.0888	0.2428***	0.1409***	0.3529***
	(1.41)	(1.10)	(4.65)	(2.86)	(9.62)
			R^2		
Junk	0.3034	0.2555	0.2245	0.2850	0.2680
Q2	0.4021	0.4295	0.2552	0.3696	0.4126
Q3	0.5352	0.5004	0.4388	0.5253	0.6439
Q4	0.6016	0.6509	0.6592	0.7278	0.6672
Quality	0.6070	0.8603	0.8192	0.6995	0.7420

The table reports regression results of 25 portfolios formed on size and quality on the market factor MKT, its lagged value, the size factor SMB, the value factor HML, the momentum factor MOM and the quality factor QMJ. Portfolios are constructed by indepentent sorts of all Swedish common stocks on market capitalization every June and monthly sorts on quality scores following Asness et al. (2014).

Appendix A9: Monthly Summary Statistics of Factor Portfolios - Norway, Denmark, Finland and the Nordics

	Total Stocks	Minimum Stocks	Max Stocks	Average Stocks	Average Return (t-statistic)	Standard Deviation	Sharpe Ratio
Panel A: Norway							
MKT	581	24	242	156	0.21% (0.63)	6.45%	0.0333
SMB	510	19	210	136	-0.02% (-0.10)	4.25%	-0.0053
HML	510	12	126	82	0.24% (0.81)	5.55%	0.0433
MOM	531	14	130	85	1.53%*** (4.10)	6.99%	0.2181
QMJ	549	14	136	91	0.73%*** (2.44)	5.66%	0.1297
Panel B: Denmark							
MKT	398	27	239	179	0.25% (0.91)	5.07%	0.0485
SMB	385	27	230	167	-0.21% (-1.03)	3.78%	-0.0545
HML	385	16	138	100	0.20% (0.85)	4.45%	0.0449
MOM	390	16	140	103	1.26%*** (4.38)	5.41%	0.2328
QMJ	393	16	144	105	0.91%*** (3.59)	4.79%	0.1907
Panel C: Finland							
MKT	241	95	156	128	0.40% (0.84)	7.70%	0.0513
SMB	227	85	152	119	-0.16% (-0.58)	4.56%	-0.0351
HML	227	52	92	72	0.30% (0.73)	6.68%	0.0445
MOM	228	30	90	73	1.36%*** (3.51)	6.39%	0.2135
QMJ	238	56	94	77	0.38% (1.12)	5.54%	0.0682
Panel D: Nordics							
MKT	2309	76	1081	743	0.22% (0.72)	5.79%	0.0381
SMB	2095	71	1015	664	-0.35%** (-2.09)	3.17%	-0.1113
HML	2095	42	610	398	0.63%*** (2.63)	4.48%	0.1399
MOM	2138	44	602	410	1.37%*** (4.39)	5.86%	0.2331
QMJ	2235	46	636	436	0.82%*** (4.11)	3.77%	0.2186

*significance at the 10% level **significance at the 5% level ***significance at the 1% level
Total stocks refers to the number of stocks for which required data is available to build the market factor (MKT), small-minus-big or size factor (SMB), high-minus-low or value factor (HML), momentum factor (MOM) and quality-minus-junk factor (QMJ). Minimum, maximum and average stocks refer to stocks per month that are included in the factor portfolios. Average return is calculated as the average of value-weighted monthly returns and standard deviation is computed from these monthly returns. Sharpe ratio is shown in its monthly form as well. T-statistics of average returns are presented in parenthesis. All data refers to the sample period from July 1986 to December 2015 with the exception of Finland, where the sample period starts in July 1993 due to limited data for early years.

Appendix A10: The Size Effect Controlling for Quality - Norway, Denmark, Finland and the Nordics

$$SMB_t = \alpha + \beta MKT_t + \beta_{-1} MKT_{t-1} + hHML_t + mMOM_t + qQMJ_t + \epsilon_t$$

Panel A: Norway

	α	β	β_{-1}	h	m	q	R^2
Full Sample	0.0003	-0.2400***					0.1325
(1986-2015)	(0.14)	(-7.33)					
	0.0000	-0.2658***	0.1384***				0.1751
	(0.01)	(-8.17)	(4.26)				
	0.0011	-0.2687***	0.1761***	-0.2264***	-0.0389		0.2633
	(0.53)	(-8.58)	(5.60)	(-6.30)	(-1.37)		
	0.0019	-0.3061***	0.1740***	-0.2726***	-0.0144	-0.1439***	0.2901
	(0.98)	(-9.43)	(5.63)	(-7.26)	(-0.50)	(-3.63)	

Panel B: Denmark

	α	β	β_{-1}	h	m	q	R^2
Full Sample	-0.0014	-0.2788***					0.1395
(1986-2015)	(-0.74)	(-7.55)					
	-0.0017	-0.3062***	0.1865***				0.2008
	(-0.97)	(-8.50)	(5.19)				
	-0.0006	-0.3102***	0.1969***	-0.2061***	-0.0604*		0.2598
	(-0.33)	(-8.91)	(5.65)	(-5.18)	(-1.84)		
	0.0008	-0.3389***	0.1819***	-0.2616***	-0.0081	-0.2026***	0.3112
	(0.47)	(-9.94)	(5.38)	(-6.55)	(-0.24)	(-5.10)	

Panel C: Finland

	α	β	β_{-1}	h	m	q	R^2
Full Sample	-0.0003	-0.3349***					0.3209
(1986-2015)	(-0.12)	(-11.25)					
	-0.0007	-0.3628***	0.1296***				0.3667
	(-0.30)	(-12.30)	(4.40)				
	0.0000	-0.3998***	0.1278***	-0.0731*	-0.0252		0.3768
	(0.02)	(-11.63)	(4.35)	(-1.90)	(-0.71)		
	0.0008	-0.4181***	0.1211***	-0.1635***	-0.0116	-0.1441***	0.3935
	(0.34)	(-12.07)	(4.16)	(-3.22)	(-0.33)	(-2.70)	

Panel D: Nordics

	α	β	β_{-1}	h	m	q	R^2
Full Sample	-0.0030**	-0.2271***					0.1719
(1986-2015)	(-1.97)	(-8.55)					
	-0.0033**	-0.2657***	0.1671***				0.2599
	(-2.28)	(-10.28)	(6.46)				
	-0.0031**	-0.2759***	0.1665***	-0.0629*	0.0144		0.2678
	(-2.05)	(-9.96)	(6.45)	(-1.86)	(0.56)		
	-0.0014	-0.3311***	0.1523***	-0.1048***	0.0429*	-0.1979***	0.3061
	(-0.95)	(-11.11)	(6.00)	(-3.05)	(1.66)	(-4.38)	

*significance at the 10% level **significance at the 5% level ***significance at the 1% level
The table presents time series regressions of SMB on different sets of factors including the market factor MKT, its lagged value, the value factor HML, the momentum factor MOM and the quality factor QMJ. T-statistics are shown in parenthesis below their corresponding coefficients. Regressions are performed for the full sample period from July 1986 until December 2015. Panel A, B and C report results for the individual countries Norway, Denmark and Finland. Panel D shows results for the Nordic region, which comprises all Swedish, Norwegian, Danish and Finish common stocks.

Appendix A11: SMB Seasonality Effects in the Nordics

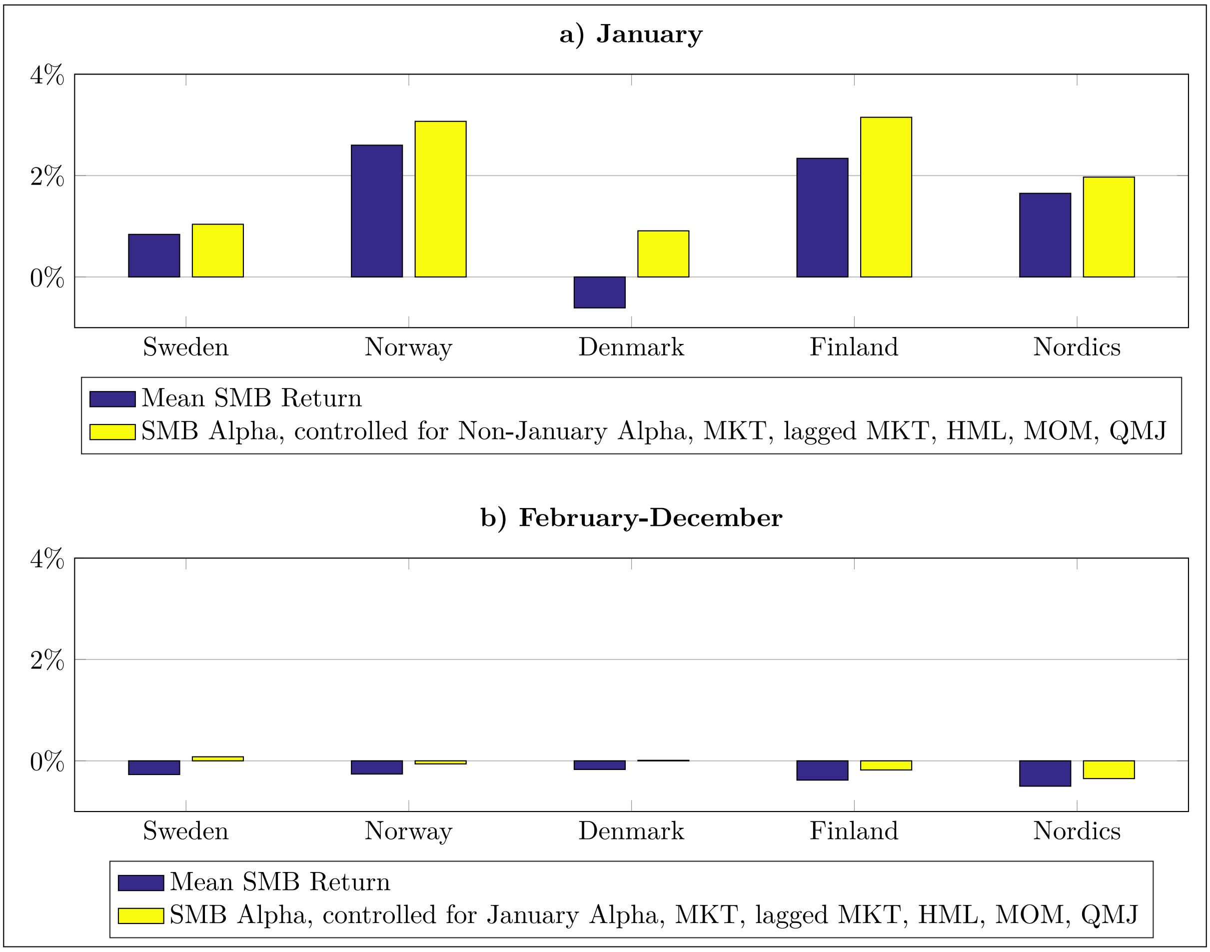


Chart a) shows monthly average SMB January returns for Sweden, Norway, Denmark, Finland and the Nordics as a whole. Moreover, it shows January regression alphas of SMB regressed on a non-January dummy variable, the market factor, its lagged value, HML, MOM and QMJ. Chart b) displays monthly average SMB returns for February till December as well as non-January regression alphas of the above described regression.

Appendix A12: Dissection into Size and Quality/Junk - Nordics

Panel A: Summary Statistics

	μ (t-statistic)	σ	Sharpe Ratio
$SmallJunk$	-0.82%** (-2.27)	6.78%	-0.1205
$BigJunk$	0.11% (0.26)	7.81%	0.0138
$SmallNeutral$	0.06% (0.23)	5.01%	0.0120
$BigNeutral$	0.12% (0.36)	6.08%	0.0191
$SmallQuality$	0.24% (0.88)	5.09%	0.0466
$BigQuality$	0.70%** (2.24)	5.90%	0.1190

Panel B: 2x3 Size-Quality Sort Portfolio Regressions

$$= \alpha + \beta MKT_t + \beta_{-1} MKT_{t-1} + sSMB_t + hHML_t + mMOM_t + qQMJ_t + \epsilon_t$$

	α	β	β_{-1}	s	h	m	q	R^2
$SmallJunk_t$	-0.0034***	1.0398***	0.0081	0.8906***	0.0818***	-0.0707***	-0.4197***	0.9041
	(-2.82)	(37.64)	(0.38)	(20.86)	(2.95)	(-3.43)	(-11.35)	
$BigJunk_t$	0.0049***	0.3913***	-0.0117	-0.2283***	-0.0201	0.0103	-0.8098***	0.9241
	(3.94)	(32.93)	(-0.54)	(-5.22)	(-0.71)	(0.49)	(-21.39)	
$SmallNeutral_t$	-0.0007	0.9538***	0.0055	0.8152***	0.3213***	-0.0354**	0.0591**	0.8984
	(-0.71)	(45.45)	(0.34)	(25.13)	(15.25)	(-2.26)	(2.10)	
$BigNeutral_t$	-0.0016*	0.9988***	0.0279*	-0.0525	0.0508**	0.0182	-0.0281	0.9273
	(-1.71)	(46.35)	(1.68)	(-1.58)	(2.35)	(1.13)	(-0.98)	
$SmallQuality_t$	-0.0002	0.9542***	0.0722***	0.6452***	0.1889***	-0.0223	0.2094***	0.8414
	(-0.20)	(35.80)	(3.53)	(15.66)	(7.09)	(-1.12)	(5.87)	
$BigQuality_t$	0.0017	1.0170***	-0.0758***	0.0171	-0.1282***	-0.0382*	0.5611***	0.8698
	(1.39)	(36.35)	(-3.52)	(0.39)	(-4.56)	(-1.83)	(14.98)	

*significance at the 10% level **significance at the 5% level ***significance at the 1% level

The table covers six portfolios constructed from independent size and qualtiy sorts. The two quality and the two junk portfolios are used to build the QMJ factor. Panel A presents summary statistics for the six portfolios. The average value-weighted return (μ) and its t-statistic, standard deviation (σ) and the resulting Sharpe ratio are shown. Panel B reports regression results for each of the six portfolios on the market factor MKT, its lagged value, the size factor SMB, the value factor HML, the momentum factor MOM and the quality factor QMJ. T-statistics are shown in parenthesis below their corresponding coefficients.

Appendix A13: Dissection into Size and Quality/Junk - Norway

Panel A: Summary Statistics

	μ (t-statistic)	σ	Sharpe Ratio
SmallJunk	-0.74% (-1.64)	8.45%	-0.0873
BigJunk	-0.21% (-0.37)	10.65%	-0.0195
SmallNeutral	-0.06% (-0.20)	6.17%	-0.0104
BigNeutral	0.21% (0.57)	7.02%	0.0302
SmallQuality	0.07% (0.22)	6.04%	0.0116
BigQuality	0.45% (1.22)	7.03%	0.0646

Panel B: 2x3 Size-Quality Sort Portfolio Regressions

$$= \alpha + \beta MKT_t + \beta_{-1} MKT_{t-1} + sSMB_t + hHML_t + mMOM_t + qQMJ_t + \epsilon_t$$

	α	β	β_{-1}	s	h	m	q	R^2
$SmallJunk_t$	-0.0051***	1.0196***	0.0372	0.7834***	0.1284***	-0.1025***	-0.4232***	0.8368
	(-2.70)	(29.37)	(1.21)	(15.30)	(3.34)	(-3.74)	(-10.98)	
$BigJunk_t$	0.0025	0.8785***	0.0468	-0.3751***	-0.0748	0.0695**	-1.0252***	0.8461
	(1.08)	(20.69)	(1.24)	(-5.99)	(-1.59)	(2.07)	(-21.74)	
$SmallNeutral_t$	-0.0027*	0.8852***	0.0287	0.5197***	0.2036***	-0.0197	0.0040	0.7817
	(-1.69)	(30.17)	(1.10)	(12.02)	(6.26)	(-0.85)	(0.12)	
$BigNeutral_t$	0.0012	0.9790***	-0.0043	-0.1224***	0.0308	-0.0877***	0.0113	0.8950
	(0.93)	(42.34)	(-0.21)	(-3.59)	(1.20)	(-4.80)	(0.44)	
$SmallQuality_t$	-0.0018	0.8245***	0.0804**	0.3784***	0.0667*	-0.0758***	0.2249***	0.6498
	(-0.92)	(22.67)	(2.49)	(7.06)	(1.65)	(-2.64)	(5.57)	
$BigQuality_t$	-0.0008	1.0736***	0.0037	0.0299	-0.0130	0.0428*	0.3267***	0.8374
	(-0.50)	(37.26)	(0.13)	(0.70)	(-0.41)	(1.88)	(10.21)	

*significance at the 10% level **significance at the 5% level ***significance at the 1% level

The table covers six portfolios constructed from independent size and qualtiy sorts. The two quality and the two junk portfolios are used to build the QMJ factor. Panel A presents summary statistics for the six portfolios. The average value-weighted return (μ) and its t-statistic, standard deviation (σ) and the resulting Sharpe ratio are shown. Panel B reports regression results for each of the six portfolios on the market factor MKT, its lagged value, the size factor SMB, the value factor HML, the momentum factor MOM and the quality factor QMJ. T-statistics are shown in parenthesis below their corresponding coefficients.

Appendix A14: Dissection into Size and Quality/Junk - Denmark

Panel A: Summary Statistics

	μ (t-statistic)	σ	Sharpe Ratio
SmallJunk	-0.84%** (-2.28)	6.95%	-0.1213
BigJunk	0.08% (0.19)	7.71%	0.0100
SmallNeutral	-0.20% (-0.65)	5.90%	-0.0347
BigNeutral	0.18% (0.56)	5.89%	0.0299
SmallQuality	0.30%(1.03)	5.53%	0.0549
BigQuality	0.76%*** (2.60)	5.49%	0.1380

Panel B: 2x3 Size-Quality Sort Portfolio Regressions

$$= \alpha + \beta MKT_t + \beta_{-1} MKT_{t-1} + sSMB_t + hHML_t + mMOM_t + qQMJ_t + \epsilon_t$$

	α	β	β_{-1}	s	h	m	q	R^2
$SmallJunk_t$	-0.0036**	0.9963***	0.0231	0.7976***	-0.0740*	-0.0004	-0.6105***	0.8203
	(-2.15)	(27.41)	(0.70)	(15.82)	(-1.86)	(-0.01)	(-15.75)	
$BigJunk_t$	0.0066***	0.9148***	0.0156	-0.3131***	0.0672	-0.2280***	-0.6570***	0.8022
	(3.42)	(21.62)	(0.41)	(-5.34)	(1.45)	(-6.25)	-(14.56)	
$SmallNeutral_t$	-0.0034*	0.9672***	0.0089	0.6953***	0.1743***	0.0344	-0.0423	0.6229
	(-1.67)	(21.65)	(0.22)	(11.22)	(3.56)	(0.89)	(-0.89)	
$BigNeutral_t$	-0.0002	0.9988***	-0.0135	-0.0426	0.1174***	0.0352	-0.1386***	0.8113
	(-0.11)	(31.64)	(-0.47)	(-0.97)	(3.39)	(1.29)	(-4.12)	
$SmallQuality_t$	0.0004	0.9665***	0.0676*	0.5309***	0.1113**	-0.1467***	0.3080***	0.6647
	(0.23)	(24.47)	(1.88)	(9.69)	(2.57)	(-4.31)	(7.31)	
$BigQuality_t$	0.0026**	0.9447***	-0.0288	-0.0464	-0.1180***	-0.0817***	0.4245***	0.8174
	(1.99)	(32.61)	(-1.09)	(-1.16)	(-3.72)	(-3.27)	(13.74)	

*significance at the 10% level **significance at the 5% level ***significance at the 1% level

The table covers six portfolios constructed from independent size and qualtiy sorts. The two quality and the two junk portfolios are used to build the QMJ factor. Panel A presents summary statistics for the six portfolios. The average value-weighted return (μ) and its t-statistic, standard deviation (σ) and the resulting Sharpe ratio are shown. Panel B reports regression results for each of the six portfolios on the market factor MKT, its lagged value, the size factor SMB, the value factor HML, the momentum factor MOM and the quality factor QMJ. T-statistics are shown in parenthesis below their corresponding coefficients.

Appendix A15: Dissection into Size and Quality/Junk - Finland

Panel A: Summary Statistics

	μ (t-statistic)	σ	Sharpe Ratio
SmallJunk	-0.06% (-0.14)	6.69%	-0.0085
BigJunk	0.33% (0.53)	10.16%	0.0324
SmallNeutral	0.48% (1.48)	5.30%	0.0900
BigNeutral	0.50% (1.18)	7.02%	0.0717
SmallQuality	0.58% (1.59)	5.96%	0.0968
BigQuality	0.45% (0.78)	9.54%	0.0473

Panel B: 2x3 Size-Quality Sort Portfolio Regressions

$$= \alpha + \beta MKT_t + \beta_{-1} MKT_{t-1} + sSMB_t + hHML_t + mMOM_t + qQMJ_t + \epsilon_t$$

	α	β	β_{-1}	s	h	m	q	R^2
$SmallJunk_t$	-0.0030	0.9800***	0.0292	0.8270***	0.3204***	-0.0228	-0.2321***	0.7779
	(-1.49)	(25.50)	(1.09)	(15.09)	(6.96)	(-0.72)	(-4.81)	
$BigJunk_t$	0.0035	0.9392***	0.0397	-0.1648**	-0.0772	0.0267	-1.1787***	0.8216
	(1.27)	(17.97)	(1.09)	(-2.21)	(-1.23)	(0.62)	(-17.97)	
$SmallNeutral_t$	0.0010	0.8712***	-0.0098	0.7290***	0.4049***	0.0277	-0.0033	0.8139
	(0.66)	(31.26)	(-0.51)	(18.34)	(12.12)	(1.20)	(-0.09)	
$BigNeutral_t$	0.0006	0.8469***	0.0318	0.0727	0.2815***	0.0623	-0.1571**	0.6564
	(0.22)	(16.89)	(0.91)	(1.02)	(4.68)	(1.50)	(-2.50)	
$SmallQuality_t$	0.0022	0.8722***	0.0813***	0.7793***	0.2304***	-0.0009	0.1005**	0.7603
	(1.17)	(24.51)	(3.28)	(15.36)	(5.40)	(-0.03)	(2.25)	
$BigQuality_t$	-0.0017	1.0470***	-0.0124	-0.1170**	0.0128	0.0049	0.4887***	0.9220
	(-1.01)	(32.25)	(-0.55)	(-2.53)	(0.33)	(0.18)	(12.00)	

*significance at the 10% level **significance at the 5% level ***significance at the 1% level

The table covers six portfolios constructed from independent size and qualtiy sorts. The two quality and the two junk portfolios are used to build the QMJ factor. Panel A presents summary statistics for the six portfolios. The average value-weighted return (μ) and its t-statistic, standard deviation (σ) and the resulting Sharpe ratio are shown. Panel B reports regression results for each of the six portfolios on the market factor MKT, its lagged value, the size factor SMB, the value factor HML, the momentum factor MOM and the quality factor QMJ. T-statistics are shown in parenthesis below their corresponding coefficients.

Appendix A16: The Size Effect Controlling for Quality - 80th Percentile of Total Stocks Applied as Size Breakpoint in Portfolio Construction

Panel A: Adding QMJ

$$SMB_t = \alpha + \beta MKT_t + \beta_{-1} MKT_{t-1} + hHML_t + mMOM_t + qQMJ_t + \epsilon_t$$

	α	β	β_{-1}	h	m	q	R^2
Full Sample (1986-2015)	-0.0061*** (-3.03)	-0.0869*** (-2.90)					0.0234
	-0.0065*** (-3.31)	-0.1069*** (-3.65)	0.1422*** (4.84)				0.0847
	-0.0050** (-2.49)	-0.1319*** (-4.24)	0.1489*** (5.10)	-0.0434 (-1.35)	-0.0684** (-2.41)		0.1043
	-0.0049** (-2.39)	-0.1352*** (-4.32)	0.1493*** (5.11)	-0.0419 (-1.30)	-0.0570* (-1.85)	-0.0359 (-0.93)	0.1065
Sub-Period 1 (1986-1999)	-0.0050 (-1.54)	-0.0839* (-1.93)					0.0228
	-0.0055* (-1.70)	-0.1018** (-2.36)	0.1162*** (2.66)				0.0644
	-0.0034 (-1.06)	-0.1488*** (-3.21)	0.1272*** (2.98)	0.0107 (0.22)	-0.1644*** (-3.17)		0.1233
	-0.0032 (-1.00)	-0.1502*** (-3.24)	0.1291*** (3.02)	0.0167 (0.34)	-0.1466*** (-2.66)	-0.0502 (-0.97)	0.1286
Sub-Period 2 (2000-2015)	-0.0071*** (-2.78)	-0.0922** (-2.20)					0.0248
	-0.0074*** (-3.01)	-0.1133*** (-2.81)	0.1726*** (4.35)				0.1135
	-0.0045* (-1.75)	-0.1853*** (-4.03)	0.1806*** (4.67)	-0.1919*** (-3.77)	-0.0166 (-0.36)		0.1769
	-0.0038 (-1.46)	-0.2058*** (-4.16)	0.1769*** (4.65)	-0.2056*** (-3.93)	0.0085 (0.23)	-0.0701 (-1.12)	0.1824

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Appendix A16: (continued)

Panel B: Subcomponents of QMJ

$$SMB_t = \alpha + \beta MKT_t + \beta_{-1} MKT_{t-1} + hHML_t + mMOM_t + qQ_t + \epsilon_t$$

	α	β	β_{-1}	h	m	q	R^2
Q = *Profitability*	-0.0041**	-0.1248***	0.1435***	-0.0375	-0.0476*	-0.1154***	0.1266
	(-2.00)	(-4.05)	(4.96)	(-1.17)	(-1.65)	(-2.98)	
Q = *Growth*	-0.0051**	-0.1336***	0.1491***	-0.0400	-0.0716**	0.0444	0.1069
	(-2.50)	(-4.29)	(5.10)	(-1.23)	(-2.51)	(1.01)	
Q = *Safety*	-0.0045**	-0.1487***	0.1494***	-0.0545*	-0.0453	-0.0798*	0.1129
	(-2.21)	(-4.60)	(5.13)	(-1.67)	(-1.46)	(-1.84)	
Q = *Payout*	-0.0049**	-0.1357***	0.1474***	-0.0387	-0.0652**	-0.0288	0.1051
	(-2.42)	(-4.26)	(5.02)	(-1.16)	(-2.26)	(-0.57)	

Panel C: Fama and French (2015a) Five-Factor Model and QMJ

$$SMB_t = \alpha + \beta MKT_t + \beta_{-1} MKT_{t-1} + hHML_t + mMOM_t + rRMW_t + cCMA_t + qQMJ_t + \epsilon_t$$

	α	β	β_{-1}	h	m	r	c	q	R^2
Full Sample	-0.0035*	-0.1504***	0.1374***	-0.0013	-0.0522*	-0.1062***	-0.1237***		0.1394
(1986-2015)	(-1.70)	(-4.76)	(4.75)	(-0.04)	(-1.81)	(-3.20)	(-2.58)		
	-0.0034*	-0.1516***	0.1376***	0.0009	-0.0454	-0.1023***	-0.1264***	-0.0247	0.1404
	(-1.66)	(-4.78)	(4.75)	(0.02)	(-1.48)	(-3.03)	(-2.62)	(-0.63)	

*significance at the 10% level **significance at the 5% level ***significance at the 1% level
The table presents time series regressions of SMB on different sets of factors, which are constructed in the Swedish market. The analysis is different compared to Table 6 only in the application of a different market value size breakpoint, which is the 80th percentile of the total number of companies. T-statistics are shown in parenthesis below their corresponding coefficients. Panel A shows regressions on the market factor MKT, its lagged value, the value factor HML, the momentum factor MOM and adds the quality factor in a final step. Regressions are performed for the full sample period from July 1986 until December 2015 as well as two sub-periods 1986-1999 and 2000-2015. Panel B shows regressions controlling for quality with one of the subcomponents of QMJ, which are the composite quality measures $Profitability$, $Growth$, $Safety$ and $Payout$. In Panel C SMB is regressed on the Fama and French (2015a) five-factor model and QMJ.

Appendix A17: The Size Effect Controlling for Quality - Conditional Sort Algorithm Applied in Portfolio Construction

Panel A: Adding QMJ

$$SMB_t = \alpha + \beta MKT_t + \beta_{-1} MKT_{t-1} + hHML_t + mMOM_t + qQMJ_t + \epsilon_t$$

	α	β	β_{-1}	h	m	q	R^2
Full Sample	-0.0010	-0.1516***					0.0622
(1986-2015)	(-0.49)	(-4.83)					
	-0.0014	-0.1720***	0.1451***				0.1179
	(-0.68)	(-5.59)	(4.71)				
	-0.0027	-0.1448***	0.1388***	0.0501	0.0711**		0.1324
	(-1.27)	(-4.29)	(4.51)	(1.44)	(2.08)		
	-0.0011	-0.1901***	0.1297***	-0.0436	0.1203***	-0.2842***	0.2275
	(-0.56)	(-5.83)	(4.45)	(1.30)	(3.62)	(-6.55)	
Sub-Period 1	-0.0023	-0.1813***					0.0744
(1986-1999)	(-0.59)	(-3.59)					
	-0.0027	-0.2017***	0.1324***				0.1121
	(-0.74)	(-4.01)	(2.60)				
	-0.0039	-0.2262***	0.1241**	0.2251***	0.1557**		0.1764
	(-1.06)	(-4.09)	(2.50)	(3.39)	(2.11)		
	-0.0017	-0.2556***	0.1284***	0.1989***	0.1925***	-0.3519***	0.3350
	(-0.51)	(-5.10)	(2.87)	(3.32)	(2.88)	(-6.10)	
Sub-Period 2	0.0001	-0.1122***					0.0452
(2000-2015)	(0.05)	(-3.00)					
	-0.0001	-0.1320***	0.1623***				0.1418
	(-0.06)	(-3.69)	(4.61)				
	-0.0005	-0.1141***	0.1535***	-0.0651	0.0766**		0.1750
	(-0.21)	(-2.75)	(4.40)	(-1.47)	(2.35)		
	-0.0001	-0.1303***	0.1487***	-0.0712	0.0871**	-0.0562	0.1776
	(-0.06)	(-2.81)	(4.19)	(-1.59)	(2.46)	(-0.78)	

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Appendix A17: (continued)

Panel B: Subcomponents of QMJ

$$SMB_t = \alpha + \beta MKT_t + \beta_{-1} MKT_{t-1} + hHML_t + mMOM_t + qQ_t + \epsilon_t$$

	α	β	β_{-1}	h	m	q	R^2
Q = *Profitability*	-0.0002	-0.1425***	0.1291***	0.0257	0.0805**	-0.2535***	0.2147
	(-0.09)	(-4.44)	(4.39)	(0.76)	(2.47)	(-6.04)	
Q = *Growth*	-0.0027	-0.1418***	0.1395***	0.465	0.0709**	-0.0396	0.1343
	(-1.26)	(-4.18)	(4.53)	(1.30)	(2.07)	(-0.89)	
Q = *Safety*	-0.0013	-0.2045***	0.1383***	0.0442	0.1119***	-0.2507***	0.2046
	(-0.64)	(-6.01)	(4.68)	(1.30)	(3.33)	(-5.62)	
Q = *Payout*	-0.0014	-0.1736***	0.1236***	0.0912**	0.0910***	-0.2545***	0.1820
	(-0.67)	(-5.20)	(4.10)	(2.57)	(2.71)	(-4.60)	

Panel C: Fama and French (2015a) Five-Factor Model and QMJ

$$SMB_t = \alpha + \beta MKT_t + \beta_{-1} MKT_{t-1} + hHML_t + mMOM_t + rRMW_t + cCMA_t + qQMJ_t + \epsilon_t$$

	α	β	β_{-1}	h	m	r	c	q	R^2
Full Sample	-0.0007	-0.1803***	0.1193***	0.1114***	0.1065***	-0.2706***	-0.1877***		0.2355
(1986-2015)	(-0.37)	(-5.60)	(4.09)	(3.08)	(3.21)	(-6.38)	(-3.79)		
	-0.0001	-0.2033***	0.1172***	0.0978***	0.1293***	-0.1902***	-0.1675***	-0.2077***	0.2784
	(-0.05)	(-6.41)	(4.13)	(2.77)	(3.96)	(-4.24)	(-3.46)	(-4.53)	

*significance at the 10% level **significance at the 5% level ***significance at the 1% level

The table presents time series regressions of SMB on different sets of factors, which are constructed in the Swedish market. The analysis is different compared to Table 6 only in the application of a conditional sort algorithm instead of using independent sorts. T-statistics are shown in parenthesis below their corresponding coefficients. Panel A shows regressions on the market factor MKT, its lagged value, the value factor HML, the momentum factor MOM and adds the quality factor in a final step. Regressions are performed for the full sample period from July 1986 until December 2015 as well as two sub-periods 1986-1999 and 2000-2015. Panel B shows regressions controlling for quality with one of the subcomponents of QMJ, which are the composite quality measures $Profitability$, $Growth$, $Safety$ and $Payout$. In Panel C SMB is regressed on the Fama and French (2015a) five-factor model and QMJ.