IS THERE A SWEDISH SIZE EFFECT?

CONTROLLING FOR QUALITY

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Abstract:

Whether size affects a firm's expected return or not has been widely disputed in asset pricing literature. However, recent evidence suggests there is a size premium in the United States. Despite this, whether a size effect exists or not remains unclear in many countries, for example in Sweden. In our paper, we test if there is a size effect in Sweden, by replicating recent literature testing for a size effect in the United States when controlling for quality. We test for a size effect in Sweden through multiple linear regression of SMB, controlling for size-dependent differences in firm quality, market risk exposure, momentum and value. Our results indicate there is no statistically significant size effect in Sweden between 1995-2019, with an SMB alpha monthly mean of –0.03% (t-statistic –0.14), when controlling for the above factors. Additionally, we find a positive relationship between size and quality, as well as the presence of a consistent quality premium in Sweden. We believe this interaction of size and quality may have previously obscured the lack of a size effect in Sweden.

Keywords:

Sweden, Quality minus junk, Size premium, SMB, Carhart four-factor model

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1. Introduction

Since the introduction of modern portfolio theory to financial economics, a large body of literature has explored whether empirical models can estimate asset prices. One such model for pricing equities is the capital asset pricing model (CAPM), introduced by Sharpe (1964) and Lintner (1965), which uses a single risk factor to estimate a firm's cost of capital. However, the CAPM does not fully explain the returns of diversified portfolios, suggesting additional factors may be needed to explain returns. One such factor is the "Small minus big" (SMB) factor, measuring the difference in returns between small and big companies. The factor dates back to Banz (1981) who first discovered an empirical anomaly that small firms tend to have higher returns than big firms. With Reinganum (1983) and Schwert (1983) confirming the anomaly across the United States equity market, the SMB factor was eventually included in empirical models explaining returns (e.g. Fama and French, 1993; Carhart, 1997). Since then, the SMB factor has had a tremendous impact on investment practice, spawning new categories of investment funds and small-cap indices (Asness, 2018).

However, the interpretation of SMB being a size effect has received widespread critique. Instead of being a size effect, critics argue the SMB factor only shows smaller firms outperforming big firms, as size proxies for other effects and risks that influence returns. This criticism against a size effect has primarily revolved around seven key findings (Asness, 2018).

First, Berk (1995, 1997) finds no relation between size and returns, when measuring size in ways besides market capitalization, which is inversely related to a firm's cost of capital. Secondly, Horowitz, Loughran and Savin (2000) show SMB's significance is concentrated in extreme stocks with market capitalization lower than $5m. Third, Chan, Karceski, and Lakonishok (2000) demonstrate that SMB has diminished after its discovery in the 1980s. Fourth, Chen, Ibbotson, Kim and Hu (2013) argue that size is merely a proxy for liquidity, and SMB reflects an illiquidity premium. Fifth, Easterday, Sen and Stephan (2009) find that SMB is significantly larger during the first trading days in January, to then rapidly decline, suggesting SMB is related to the January effect rather than size. Sixth, Israel and Moskowitz (2013) find that the size effect has a weak historical record, with a non-significant alpha relative to CAPM between 1926 and 2011. Lastly, Fama and French (2011) find that SMB is much weaker internationally, which should not occur without significant arbitrage in the price of size between markets.

In 2018, the seven above critiques against a size effect were addressed by Asness, Frazzini, Israel, Moskowitz, and Pedersen (2018a) testing for a size effect while controlling for quality.[1] They test for a size effect controlling for quality through a QMJ factor, believing the size effect has been obscured by an positive relationship between quality and size, where quality commands a premium. QMJ refers to "Quality Minus Junk", introduced by Asness, Frazzini and Pedersen (2014), a factor that when used in an SMB regression, adjusts for the empirical observation that small firms tend to be of lower quality on average. When controlling for firm quality as above, Asness et al. (2018a) find

[1] Quality is defined as characteristics that investors should be willing to pay a higher price for, everything else equal. Please see *section 1.2* for more definitions.

a significant size premium in the United States. This significant size premium affirms that size has a relation to returns in the United States and that SMB contains a pure size effect, not explained by the critics' alternative explanations.

In relation to the above critiques and findings, we test if there is a size effect in the Swedish public equity markets. We control for the same well-known market anomalies as Asness et al. (2018a) including quality through QMJ, replicating their paper but with a focus on Sweden. To perform our test, we create a six-factor model, including Carhart's four factors, a lagging market factor and the QMJ factor. We derive all factor returns from the ground up and construct portfolios following the methodology of Asness, Frazzini and Pedersen (2018b). We construct our portfolios using a sample of equities listed on major Swedish stock exchanges, between 1995 and 2019, with on average 275 Swedish firms.[2]

To determine if there is a size effect in Sweden, we run a linear regression of SMB against our model's other explanatory factors, treating the regression constant as SMB alpha. We generate coefficients on the explaining factors and adjusted R-squared, indicating the magnitude and explanatory power of the different factors against SMB. We interpret SMB alpha as the share of SMB not explained by controlling for size-dependent differences in market risk exposure, momentum, value and quality. The remaining unexplained difference (SMB alpha), we hence view as a potentially pure size effect in the Swedish equity market.

Through our tests, we expand the understanding of whether there is a size effect in Sweden. In contrast to Asness et al. (2018a) who test the United States' size effect controlling for quality, we focus on studying the Swedish size effect in-depth. For example, we determine SMB alpha in Sweden and not merely a difference in SMB alpha when controlling for QMJ.[3] Additionally, we show how SMB alpha and other relevant factors have varied over time, as well as how returns alpha varies across size deciles in Sweden (similar to the detail of the original study on the United States equity market). Our paper is to the best of our knowledge, the first paper examining in detail the Swedish size effect controlling for a QMJ factor.

1.1 Research question

We answer the following research question in the paper:

Is there a size effect in Swedish equity markets, and if there is, what is the size of this effect in the Swedish equity markets, controlling for other well-known market anomalies including quality?

[2] The dataset includes stocks listed on NASDAQ OMX Stockholm Large Cap, Mid Cap, Small Cap, and the First North Stock Exchange.

[3] Asness et al. (2018a) studied the Swedish market between 1983–2012, as part of a robustness check on many international equity markets, but only reported the magnitude of change in SMB alpha (after adding QMJ) and not actual SMB alpha for Sweden.

1.2 Relevant definitions

Throughout the paper, we often refer to the terms listed below. We use these terms in the context of our definitions, and while alternative definitions exist, they may not accurately portray our intended meaning.

Classifications are firm-specific metrics used to determine whether to include or exclude a specific firm in a subset portfolio. For example, such a metric could be *market capitalization*, and we could classify firms as either "big" or "small" depending on their relative market capitalization.

Subset portfolios are value-weighted portfolios that include firms belonging to the intersection of two classifications. We use these portfolios as components in constructing factor portfolios.

Zero-investment portfolios are combinations of subset portfolios which as a group collectively require zero investment at acquisition. These portfolios are achieved by purchasing and short-selling subset portfolios of equivalent value, resulting in a net-zero investment at time t=0.

Factors are zero-investment portfolios that aim to explain the difference in returns between firms having different classifications. For example, the SMB factor as defined below.

SMB is a "small minus big" factor, which we construct from the intersection of subset portfolios based on size and book-to-market ratios. The factor explains the difference in returns between small and big firms on a monthly basis.

SMB alpha is the regression constant's value when regressing SMB against (controlling for) other known factors influencing returns. It is the difference in returns between small and big companies not explained by other known factors.

Size effect is the term we use to describe a statistically significant SMB alpha value, regardless of whether SMB alpha has a negative or positive sign.

Size premium is the term we use to describe a size effect with a statistically significant positive SMB alpha value.

QMJ refers to a "quality minus junk" factor, which consists of subset portfolios with firms classified on size and quality. The factor helps explain the difference in returns between high quality and low quality (referred to as junk) firms.

Quality we define as a set of firm characteristics that, all else equal, investors would be willing to pay more for (see section *2.3* for the characteristics).

2. Literature review

Asset pricing theory, that is theory which aims to explain the cost of capital of firms, is a topic well-studied in financial economics literature. In the following section, we present a brief overview of this literature, focused on research relevant for our tests of a size effect.

2.1 Asset pricing models and the SMB factor

The capital asset pricing model (CAPM) was introduced in the early 1960s by Sharpe (1964) and Lintner (1965) and helps explain how firms' exposure to systematic risk relates to expected stock return. However, CAPM is unable to fully explain the returns of diversified portfolios, which suggests the existence of additional factors explaining financial returns (e.g. Fama and French, 1992; He and Ng, 1994). One early such factor was the SMB factor, which started as an empirical phenomenon in the United States first discovered by Banz (1981). Alquist, Israel and Moskowitz (2018) argue the SMB factor became the first real returns anomaly to challenge the CAPM.

Many papers have since introduced potential factors to explain returns besides CAPM (e.g. Stattman, 1980; Banz, 1981; Jegadeesh and Titman, 1993). For example, factors such as HML have been introduced, which is an observation that stocks with high book-to-market ratios tend to outperform stocks with low book-to-market ratios (Stattman, 1980).

In 1993, Fama and French (1993) created a three-factor model composed of a market factor, an SMB factor, and an HML factor to explain firms' returns as an alternative to the CAPM. Since its introduction, the three-factor model has had two significant revisions. Firstly, Carhart (1997) created a revised version of the model by introducing a fourth factor, UMD (momentum), as an explaining variable. Secondly, Fama and French (2014) added two new factors to the original model: RMW (a profitability factor) and CMA (an investment factor). For reference, these are the revised versions of the Fama French three-factor model:

Equation 1: *Carhart's Four-Factor Model*

$$R_i - R_f = \alpha_i + \beta_s SMB + \beta_m (R_m - R_f) + \beta_h HML + \beta_u UMD + \varepsilon_i$$

Equation 2: *Fama and French's Five-Factor Model*

$$R_i - R_f = \alpha_i + \beta_s SMB + \beta_m (R_m - R_f) + \beta_h HML + \beta_r RMW + \beta_c CMA + \varepsilon_i$$

Carhart (1997) finds that by including a one-year momentum factor in his asset pricing model, the explanatory power of returns in the United States improves to an adjusted R-squared of 0.933 compared to CAPM's adjusted R-squared of 0.834.[4]

2.2 Evidence against a size effect

As mentioned in the introduction, the SMB factor's inclusion in multi-factor models eventually came under heavy criticism in the United States. The criticism mainly revolves

[4] For a size decile 1 portfolio in the United States, between 1963 and 1993.

around critics believing SMB does not contain a size effect, and they base this on seven key findings (Asness, 2018).

The first critique relates to the construction of the SMB factor. Berk (1995, 1997) argues that measuring size through market capitalization is flawed, as market capitalization is both a measure of a firm's discount rate and size, which are inversely related. Berk (1995) finds that by measuring firm size with alternative metrics, there is no evidence of a relation between size and returns in the United States.[5]

Furthermore, the second critique of SMB is that a limited set of tiny firms drives the factor's significance and the unexpected returns of these firms should be attributed to reasons besides their size. For example, Knez and Ready (1997) show that SMB is concentrated in the extreme 1% of observations. Furthermore, Horowitz, Loughran, and Savin (2000) find that by excluding firms with a market capitalization lower than $5 million, SMB loses its significance in a sample between 1963-1997.

Moreover, the third critique argues that while an SMB-related size effect has existed, it diminished following its publication in 1981. For example, Chan et al. (2000) find that during 1984-1998 large-cap stocks outperform small-cap stocks in the United States. Likewise, Schwert (2003) finds that a size effect has either disappeared or become much smaller by studying the returns of a size-based trading strategy after 1982. These arguments find strength in the no-arbitrage principle, as investors became aware of the anomaly in 1981 and shortly after, the size effect disappeared.

Next, the fourth main critique of a size effect is that while it exists, size is simply a proxy for liquidity, and smaller firms generate higher returns only due to a relative illiquidity premium. For example, Chen et al. (2013) find links between size and liquidity that are especially prevalent among micro-cap stocks. Crain (2011) also proposes this illiquidity premium theory, in his review of the literature, as a possible explanation for size-related observations, such as that the smallest stocks have the largest size premium.

The fifth critique of the size effect is that SMB's significance is driven by a strong effect in January, which then rapidly declines, indicating a link between SMB and the January anomaly. For example, Keim (1983) attributes nearly 50% of the size anomaly between 1963-1979 to the January effect. The link to the January effect persists with newer data, with Easterday, Sen and Stephan (2009) finding that the January returns effect is "suitably represented by firm size".

The sixth critique against a size effect is that newer studies examining it historically, with broad data sets, have not been able to find a significant historical record for a size effect. Israel and Moskowitz (2013) examine the alpha of SMB against CAPM in the United States between 1926-2011 and find the size effect has non-significant alpha across the entire period (t-statistic 1.16), as well as in all subsets of this period. Furthermore, Israel et al. (2013) find no significant evidence that "size, value, or momentum premia have changed over time", calling into question the existence of a size effect.

[5] The alternative metrics for size tested were book assets, book PP&E, employees, and sales.

Lastly, the seventh critique against a size effect is that while it appears in the United States, it is much weaker internationally for no particular reason. For example, Barry, Goldreyer, Lockwood, and Rodriguez (2002) find no significant size effect when studying 35 emerging markets between 1985-2000.[6] Likewise, Fama and French (2011) examined SMB returns in four global regions between 1990 and 2010, finding that "the global models do not do well when asked to explain average returns on regional size-B/M or size-momentum portfolios".[7]

2.3 Quality minus junk factor

Similar to the SMB factor, Asness et al. (2014) introduced the quality minus junk (QMJ) factor in 2014. The factor builds on an empirical observation that firms of higher quality tend to outperform junk firms (of low quality). The factor consists of a zero-investment portfolio with firms categorized on quality, using a range of metrics for quality averaged into three categories: profitability, growth, and safety (Asness et al., 2018b). Previously, QMJ also included a fourth category (payout) as a measure of quality, but it was dropped in the 2018 revision of QMJ.

The profitability category contains six metrics for measuring firm profitability (Asness et al., 2018b). One of the six metrics is a *gross profit to total assets ratio*, which Novy-Marx (2013) shows is a measure of firm quality. Other metrics for profitability include *cash flow over assets* and having *low accruals*, stemming from Sloan (1996), Richardson, Sloan, Soliman, and Tuna (2005) showing that the likelihood of future earnings performance depends on the magnitude of cash and accrual components of current earnings. The remaining three metrics used for profitability are *return on equity*, *return on assets*, and *gross margin,* which are metrics based on value investing theory proposed by Graham and Dodd's security analysis book (Asness et al., 2018b).

A firm's composite quality score also contains the growth category, which has six metrics for measuring firm profitability growth (Asness et al., 2018b). The metrics are average *growth rates* of the above six profitability measures, over five years. The category builds on Mohanram (2005) showing that growing firms tend to significantly outperform the least growing (or most shrinking) firms.

Lastly, the safety category of a firm's composite quality score utilizes five metrics to measure quality through business risk (Asness et al., 2018b). The first metric is *betting against beta* (*BAB*), building on Frazzini and Pedersen (2014) showing that firms with low beta tend to have higher alpha. The second metric is having *low leverage*, which is based on Penman, Richardson, Tuna, (2007), George and Hwang (2010) highlighting that firms with low leverage tend to have higher alpha. The third and fourth metrics correspond to bankruptcy risk, as measured through the *Altman Z score* (Altman, 1968) and *Ohlson O score* (Ohlson, 1980). Asness et al. (2018b) define the metric so that lower

[6] The 35 emerging market countries were: Czech Republic, Greece, Hungary, Poland, Portugal, Russia, Slovakia, Turkey, Argentina, Brazil, Chile, Colombia, Mexico, Peru, Venezuela, Bahrain, Israel, Jordan, Oman, Saudi Arabia, Egypt, China, Sri Lanka, Taiwan, India, Indonesia, South Korea, Malaysia, Pakistan, Philippines, Thailand, Morocco, Nigeria, South Africa, Zimbabwe.

[7] The four regions were: North America (*US, Canada*); Europe (*Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, UK*); Japan; and Asia Pacific (*Australia, New Zealand, Hong Kong, Singapore*).

credit risk equals higher firm quality, based on Campbell, Hilscher, and Szilagyi (2008) showing that financially distressed firms deliver anomalously low returns. The final metric used for measuring firm safety is having *low ROE volatility*, which also is a sign of firm quality (Asness et al., 2014; 2018b).

All the three categories are combined to create a single quality score, with each metric averaged first in their category then averaged across categories, to create the composite score. Dependent on the quality score obtained, firms are categorized as quality, junk or neither, which determines QMJ portfolio allocation. For our construction of the QMJ portfolio, please see *section 3.1.3* and *3.1.5.*

2.4 Size premium controlling for quality (through QMJ)

When deriving the QMJ factor, Asness et al. (2014) found that small firms tend to be "junk" significantly more than big firms. Being curious about the implications of the finding, Asness et al. (2018a) empirically test a size effect controlling for quality in the United States and 23 international equity markets. Finding a significant size premium, they argue that their paper "Size matters if you control your junk" resurrects the size premium in the United States by directly addressing the concerns of the critics above.

In the paper, Asness et al. (2018a) find that there is a significant size premium in the United States, between 1957 and 2012, with an SMB alpha of +0.49% per month (t-statistic 4.89) when controlling for QMJ versus +0.14% (t-statistic 1.23) without QMJ. They further find that the size premium remains significant, of SMB alpha +0.83% per month (t-statistic 5.98) when measuring size by alternative measures such as book assets, addressing the critique of Berk (1995, 1997). Likewise, they find that the size premium is not concentrated in extremely small stocks, addressing the critique of Horowitz et al. (2000).

Furthermore, Asness et al. (2018a) find that the size premium is not purely a liquidity effect, as SMB alpha remains significant (t-statistic 2.03) when controlling for liquidity, addressing the findings of Chen et al. (2013). In testing for a size effect when isolating January versus non-January, they also find that their size premium is more consistent over the entire year, with a January SMB alpha of +1.57% (t-statistic 4.74) versus a non-January SMB alpha of +0.38% per month (t-statistic 3.62). Finding a size premium in February-December, they also address the critique of Easterday et al. (2009) who suggest the size effect is a disguised January effect. Furthermore, they find that the size premium has been persistent over time when controlling for quality, challenging the findings of Schwert (2003) that any size effect has diminished since the 1980s.

In addition to their findings in the United States, Asness et al. (2018a) also study the impact of controlling for QMJ on a size effect in 23 international equity markets. They find a positive increase in SMB alpha in 22 markets (all but Ireland) when controlling for quality, which addresses the weak international results critique of Barry et al. (2002).[8] The positive change in SMB alpha, however, varies in each country, with Hong Kong and

[8] The 23 international equity markets tested were: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, Norway, New Zealand, Portugal, Singapore, Spain, Sweden, Switzerland, and UK.

the United States seeing the most substantial increases in SMB alpha of +0.75% and +0.50% respectively, with Sweden at +0.10%, and with eight countries having an effect of +0.01%–0.05%.[9] These country-specific differences speak for a size effect being more prevalent in some markets than others.

3. Theoretical framework

In relation to the above findings of Asness et al. (2018a), we test if there is a size effect in Sweden. To test for the size effect, we start by constructing a theoretical model that we will regress SMB against, to examine SMB alpha. In the *sections* below, we give an overview of how we construct this model and perform our regression.

3.1 Theoretical model

Our model starts from a Carhart four-factor model, adding a QMJ and lagging excess return factor, as detailed below and similar to Asness et al. (2018a). We prefer Carhart's four-factor model over Fama and French's (2014) five-factor model, as Carhart's model does not include a profitability factor, which avoids having two factors controlling for profitability as QMJ includes a profitability metric. Starting from the Carhart four-factor model and adding our two additional factors, our theoretical model becomes:

Equation 3: *Our model*

$$R_i - R_f = \alpha_i + \beta_s SMB + \beta_q QMJ + \beta_{m_t}(MKT_t)$$
$$+\beta_{m_{t-1}}(MKT_{t-1}) + \beta_h HML + \beta_u UMD + \varepsilon_i$$

In constructing our model factors, as explained in *section 3.1.5,* we follow the methodology of Asness et al. (2018a). In deriving classifications for our factors, we also follow Asness et al. (2018a, 2018b), albeit with a few modifications outlined in *section 3.1.1 – 3.1.4.*

3.1.1 Size classification of firms

In our model, we derive factors based on two subsets of firm size (*small* and *big*), and we give equal weighting to these subsets when calculating returns for model factors, in order to examine a factor's explanatory power with regards to SMB. We categorize firms as either "small" or "big" according to total *market capitalization* relative to other Swedish firms in June every fiscal year. Firms with market capitalizations in the 1st to 70th percentile are classified as "small", and firms with market capitalizations in the 71st to 100th percentile are classified as "big". We have set the 70th percentile as a cutoff point, so the cutoff point roughly matches the median market capitalization of the NYSE (similar to Asness et al., 2018b).

3.1.2 Book-to-market ratio classification of firms

From our sample, we also classify the *relative book-to-market ratio* of firms, calculated as *book shareholders' equity* divided by total *market capitalization*. We rank firms numerically on this ratio, irrespective of size, and calculate their relative percentiles

[9] The 8 countries were: Austria, Belgium, Canada, France, Netherlands, New Zealand, Spain, and UK.

monthly. Firms with the 30% lowest ratios (1st to 30th percentile) are classified as "growth", whereas firms with the 30% largest ratios (71th to 100th percentile) are classified as "value". The firms with ratios in between these (growth and value) classifications (in the 31st to 70th percentile) are classified as "middle".

3.1.3 Quality classification of firms

Next, we generate quality scores for each firm, using the metrics for profitability, growth and safety introduced in *section 2.3*. All of the quality metrics we use from the various categories are summarized below in **Table 1.** We calculate the quality metrics using available annual accounting data, as well as monthly data on market prices.[10]

Table 1: Metrics used for firms' quality classification

	Profitability category	**Growth category**	**Safety category**
Metric #1	GPOA: Gross profits over assets	G_GPOA: five-year growth in gross profits	LEV: Minus leverage in firm
Metric #2	ROE: Return on equity	G_ROE: five-year growth in return on equity	BAB: Minus beta
Metric #3	ROA: Return on assets	G_ROA: five-year growth in return on assets	Altman_Z: Metric for bankruptcy risk
Metric #4	CFOA: Free cash flow over assets	G_CFOA: five-year growth in free cash flow over assets	EVOL: five-year standard deviation in return on equity
Metric #5	GMAR: Gross margin	G_GMAR: five-year growth in gross margin	N/A[11]
Metric #6	LACC: Minus accruals	G_LACC: five-year decrease in accruals	N/A

Table 1. Describes the firm-specific metrics used to determine the quality composite score for firms in Sweden between 1995-2019.

We convert the scores on each quality metric into a relative numerical rank that compares performance between firms, per year. Firms' numerical ranks are then used to generate standardized Z scores for each firm on each metric, as per below:

Equation 4: *Generation of Z scores for each quality metric*

$$Z_{firm\ i} = (firm\ i_{rank} - \mu_{rank}) \div (\sigma_{rank})$$

The Z scores of each metric are then averaged for each firm and year, in the quality metrics' respective categories. Afterwards, we average the Z scores of the three categories into a single measure for the quality of a firm in a specific year.

[10] For exact calculations of each metric, see appendix section 2.

[11] As we lack sufficient data to calculate the Ohlson O score (a measure of credit risk) for all firms, we drop this metric from the safety category, using instead only Altman Z to measure credit risk.

Equation(s) 5: *Averaging of Z scores across categories*

$$Z_{Profitability} = \frac{1}{6} \times (Z_{GPOA} + Z_{ROE} + Z_{ROA} + Z_{CFOA} + Z_{GMAR} + Z_{LACC})$$

$$Z_{Growth} = \frac{1}{6} \times (Z_{G\ GPOA} + Z_{G\ ROE} + Z_{G\ ROA} + Z_{G\ CFOA} + Z_{G\ GMAR} + Z_{G\ LACC})$$

$$Z_{Safety} = \frac{1}{4} \times (Z_{LEV} + Z_{BAB} + Z_{Altman\ Z} + Z_{EVOL})$$

Equation 6: *Calculating the composite quality score*

$$Quality = \frac{1}{3} \times (Z_{Profitability} + Z_{Growth} + Z_{Safety})$$

We then classify firms' *quality* as "quality", "junk", or "none", depending on their quality score and size classification. We do this by conditionally sorting on size, and then generating size-dependent quality percentiles based on a firm's composite quality score. Firms in the 1st to 30th percentile of *composite quality* scores for a year in their size category are classified as "junk", whereas the 71st to 100th percentile of scores are classified as "quality".

3.1.4 Momentum classification of firms

Additionally, we derive a (up/down) momentum classification in our sample by ranking firms' past *ten-month returns* lagged by two months (similar to Asness et al., 2018a). We rank firms numerically on their relative returns, irrespective of size, and calculate their relative ranks on a rolling monthly basis. Firms with the 30% lowest returns (1st to 30th percentile) are classified as "down", whereas firms with the 30% highest returns (71st to 100th percentile) are classified as "up".

3.1.5 Model factors

Using the above classifications and subset portfolios, we derive factor portfolios for our model. We create our factor portfolios through the intersections of subset portfolios with different *classifications* as described above. We give equal weight to all subset portfolios and take "long" positions in one of the *classifications* subsets, and "short" positions in the other *classification,* resulting in on average "zero-investment" portfolios. The net-zero investment in the factor portfolios stems from using the proceeds from short-selling one *classification's* subset portfolios, to purchase equity in the other *classification's* subset portfolios.

We calculate weighted returns on the factor portfolios every month, as the change in market capitalization of the subset portfolios, adjusting for any dividends. Therefore, our factors explain the difference in returns between firms having one *classification* and those firms with the other *classification,* on a monthly basis.

SMB factor

The "Small Minus Big" factor is based on six subset portfolios calculated from the intersection of the *size* and *book-to-market* classifications. The factor describes the difference between the returns of small and big firms. We calculate it as the arithmetic mean of the "*small*" portfolios' return minus the mean of *"big"* portfolios' return.

Equation 7: *Small minus big portfolio*

$$SMB = \frac{1}{3} \times \left(R_{Small\ value} + R_{Small\ middle} + R_{Small\ growth}\right) - \frac{1}{3} \times \left(R_{Big\ value} + R_{Big\ middle} + R_{Big\ growth}\right)$$

<u>*HML factor*</u>

The "High Minus Low" factor is based on four subset portfolios calculated from the intersection of the *book-to-market* and *size* classifications. The factor describes the difference between the returns of value and growth firms. We calculate it as the arithmetic mean of the "*value*" portfolios' return minus the mean of *"growth"* portfolios' return.

Equation 8: *High minus low portfolio*

$$HML = \frac{1}{2} \times \left(R_{Small\ value} + R_{Big\ value}\right) - \frac{1}{2} \times \left(R_{Small\ growth} + R_{Big\ growth}\right)$$

<u>*QMJ factor*</u>

The "Quality Minus Junk" factor is based on four subset portfolios calculated from the intersection of the *quality* and *size* classifications. The factor describes the difference between returns of quality and junk firms. We calculate it as the arithmetic mean of the "*quality*" portfolios' return minus the mean of *"junk"* portfolios' return.

Equation 9: *Quality minus junk portfolio*

$$QMJ = \frac{1}{2} \times \left(R_{Small\ quality} + R_{Big\ quality}\right) - \frac{1}{2} \times \left(R_{Small\ junk} + R_{Big\ junk}\right)$$

<u>*UMD factor*</u>

The "Up Minus Down" factor is based on four subset portfolios calculated from the intersection of the *momentum* and *size* classifications. The factor describes the difference between the returns of firms having positive and negative momentum. We calculate it as the arithmetic mean of the "*up*" portfolios' return minus the mean of *"down"* portfolios' return.

Equation 10: *Up minus down (momentum) portfolio*

$$UMD = \frac{1}{2} \times \left(R_{Small\ up} + R_{Big\ up}\right) - \frac{1}{2} \times \left(R_{Small\ down} + R_{Big\ down}\right)$$

<u>*MKT and lagging MKT factor*</u>

In contrast to the other factors above, our two final factors (MKT and lagging MKT) does not use the above *classifications*. Instead, the market factors describe excess returns on the Swedish stock market. They are calculated as long portfolios consisting of two elements, the returns of the OMXSPI Stockholm index and the yield of 1M Swedish T-bills. We calculate the factors on a monthly basis, as the monthly return of the stock market index minus the risk-free rate's monthly yield.

We include the MKT factor to control for differences in market risk, by including the Swedish stock market index's excess returns in our regression. We include our lagging market factor to control for the possibility of illiquid firms experiencing lead-lags in their price response to macroeconomic news (similar to Asness et al., 2018a).

Equations 11: *MKT (Market excess return) portfolio*

$$MKT_{(t)} = (R_m - R_f)_{(t)} = (R_{OMXSPI})_{(t)} - (Yield_{\ SWE\ 1M\ T-bill})_{(t)}$$

$$MKT_{(t-1)} = (R_m - R_f)_{(t-1)} = (R_{OMXSPI})_{(t-1)} - (Yield_{\ SWE\ 1M\ T-bill})_{(t-1)}$$

where t is equal to the current month

3.2 Statistical regression to isolate SMB alpha

Using our theoretical model with the above derived factors, we determine if there is a size effect in the Swedish equity markets through multiple linear regression. By regressing SMB (dependent variable) against our other factors (independent variables), the regression explains how differences in returns between small and big firms (SMB) arise.

Equation 12: *SMB regression against Carhart, lagged MKT, and QMJ*

$$SMB = \alpha + \beta_{m_t}(MKT_t) + \beta_{\boldsymbol{m_{t-1}}}(MKT_{t-1}) + \beta_h HML + \beta_u UMD + \beta_q QMJ + \varepsilon$$

The regression yields coefficients for each of the factors and a regression constant.[12] The regression also provides measures for the explanatory power of the regression (adjusted R-squared) and the certainty (t-statistic) that a coefficient differs from zero (our null hypothesis). We treat individual variables as statistically significant if the absolute value of the t-statistic > 2.00 (p-value <0.05) in line with academic convention. If variables are not statistically significant, we do not reject the null hypothesis or make a distinction whether the coefficient should be zero or not.[13]

The different coefficients' signs correspond to observed differences between big and small firms in the underlying factors/explanatory variables. For example, a negative QMJ coefficient would indicate smaller firms having lower quality than big firms on average. Our regression constant (SMB alpha), therefore, represents the difference in returns of small and big firms that cannot be explained as differences in:

a) Momentum between small and big firms (UMD explanatory variable controls for this)
b) Quality between small and big firms (QMJ explanatory variable controls for this)
c) BE/ME ratios between small and big firms (HML explanatory variable controls for this)
d) Market risk / systematic risk exposure between small and big firms

If the regression constant is statistically significant, we treat it as a size effect for small firms in the Swedish equity markets in accordance with Asness et al. (2018a). Therefore, it is SMB alpha (the regression constant) that we investigate empirically in our tests below.

[12] For the exact definition for the size effect, see section 1.2.
[13] The null hypothesis being that the coefficient/factor does not explain variation in SMB, hence equals zero.

4. Empirical test

4.1 Data and processing

Performing our empirical tests, we calculate all factors and metrics from the ground up, using raw data from the Compustat - Capital IQ, Thomson Reuters Eikon and Riksbanken databases. We process the raw data as outlined below to ensure the sample's appropriateness for empirical analysis.

To perform our empirical tests, we use all available accounting and market data on Compustat for Swedish equities in the available time interval (1987-2019). For accounting data, we use annual figures, and for market data, we use the daily securities data on all available equity securities (multi-class shares included) for each Swedish firm in the database. Besides data on equities, we also use the Thomson Reuters Eikon database for the daily price of the OMXSPI index between 1987-2019, and the Swedish Riksbank website for the daily trading yield on the Swedish 1M T-bill between 1983-2019.

We process the raw accounting data by dropping any duplicate observations for a single fiscal year, keeping the latest available data. If *some* accounting data is missing for a firm, we keep the observation, but individual metrics that lack sufficient data to calculate we set as missing (e.g. ROE can be set as missing), similar to Asness et al. (2018b). Next, we proceed to process the raw market data. We drop observations that are not common shares or do not have a claim on a company's earnings, as our model is not applicable to these securities (similar to Asness et al., 2018a). We also drop non-primary securities from our data sample, if firms have multi-class share structures, after calculating firms' total market capitalization. We use this method because a firm's primary shares tend to be more liquid and have up-to-date price information, which is better for calculating returns. Next, we sort our observations by firm and date, dropping all observations that are not the last observation in a specific month. This way, we keep only one price observation per firm, in a specific year and month, which we use to generate monthly returns. Monthly returns are calculated for all firms when a new price is available (excluding prices carried forward).

After this first round of data processing, we require firms to have at least one measure available in each category (one quality metric in profitability, one in growth, and one in safety), to generate a quality score (ignoring missing values). Observations without a generated quality score cannot be assigned into quality deciles, which is required to construct the QMJ portfolio. Therefore, we drop these observations. We also drop three extreme outliers, setting observations' returns missing if their monthly return exceeds +1000%. We proceed to generate our factor portfolios, then lastly, drop portfolios generated before 1995 due to the very limited sample size before 1995.[14] In order to see the exact breakdown of the number of observations dropped in each step, please see the data processing section in Appendix 2.

[14] The first year we include in our analysis is 1995, which uses 65 firms in our sample to generate factors.

4.2 Methodology

In this section, we outline how we generate our metrics, construct our subset portfolios, and derive our factors. We process data and drop observations according to the steps outlined in the data processing section above. We calculate our quality, size and book-to-market metrics and generate portfolios based on the methodology of Asness et al. (2018a, 2018b), with modifications as outlined in *section 3* and *appendix section 2*.

In doing this, we start by calculating accounting-based and market-based quality metrics, returns and size classifications. We use the accounting data to calculate profitability and growth metrics, as well as the leverage and EVOL safety metric.[15] Additionally, we use the accounting data as components to calculate the Altman Z score and book-to-market ratios. We use market data to calculate returns, size (market capitalization), beta, and as a component for Altman Z score and book-to-market ratios.

We then perform sanity checks for all quality metrics and generate the composite quality scores for all firms.[16] Next, we combine our data sets through merging our accounting and market data. We match our accounting data to market data by date, aligning accounting data for fiscal year *t-1* to price observations between June 1st year *t-1* to May 31st *year t*. Through the alignment, we assume that an equal half of a fiscal year's revenues and costs occur in the first half of the year, an assumption that Asness et al. (2018b) also make.

We then create our subset portfolios by including firms based on the intersections of relative market capitalization (size), quality, momentum and book-to-market ratios. Firms in categories which correspond to specific subset portfolios (e.g. small and value) are marked with an include flag and are included in the construction of the portfolio. Included firms are value-weighted, according to the firm's market capitalization in the previous month, and rebalanced monthly. We then calculate the total return of each subset portfolio every month as the difference in the price of each security multiplied by its relative weight in the portfolio. We adjust stock prices to correct for dividends or stock splits, ensuring returns are calculated as accurately as possible.[17] Then, we generate factor portfolios by arithmetically averaging the returns of our long and short subset portfolios as per *section 3.1.5*.

Lastly, we regress our derived factors using multiple linear regression per year and month, to generate our relevant outputs. We then perform tests on the factor portfolios for heteroscedasticity, autocorrelation, and multicollinearity, finding only a slight issue with heteroscedasticity.[18] We also perform a series of robustness checks, comparing our

[15] For exact metric calculations, please see appendix section 2.
[16] If a sanity check is breached, we replace the metric's value with a missing value, thus excluding it from Z score calculations. Examples of sanity checks on metrics include a) not having negative equity; b) having positive revenue; and etc.
[17] We calculate returns using the Compustat formula:

$$((prccd \div ajexdi) \times trfd) \div ((prccd_{[t-1]} \div ajexdi_{[t-1]}) \times trfd_{[t-1]}) - 1.$$

[18] Multiple linear regression assumes the sample has homoscedasticity, no autocorrelation, and no multicollinearity. Our factor portfolios undergo tests for these factors, see appendix section 4 for results.

derived factors with data on these factors from the Swedish House of Finance, and our results appear robust through time.[19]

4.3 Main results and discussion

After deriving our factors as above, we begin by testing our Swedish SMB factor in *section 4.3.1* for statistical significance between 1995 to 2019, also testing for a potential January effect. In *section 4.3.2*, we perform a regression of SMB controlling for our model's other factors, testing SMB alpha. In *section 4.3.3*, we compare our regression's results to the United States results of Asness et al. (2018a). Furthermore, in *section 4.3.4,* we examine how SMB, SMB alpha and QMJ have varied over time in Sweden and discuss potential explanations for this variation. We also look closer at the interaction between SMB and QMJ. In *section 4.3.5,* we analyze the distribution of quality and size in our sample and discuss potential explanations for the test results of the regression. Finally, in *section 4.3.6*, we proceed to examine returns' alpha across size deciles to test the linearity of quality's correlation with size.

<u>4.3.1 The SMB factor in Sweden</u>

In line with Banz (1981), we hypothesize that we will find 1*a) a positive difference between the returns of small and big firms on average for the duration of our test*. As discussed, this difference in returns (SMB) may have many potential explanations; for example, smaller firms may have a higher risk, lower liquidity, and lower firm quality. Furthermore, we hypothesize that 1*b) SMB could be driven by a disguised January effect, so we expect to find a stronger SMB effect in January, as per Keim (1983)*.

We perform our test on the Swedish "Small minus big" (SMB) factor and do not find a statistically significant (t-statistic –1.69) SMB monthly return in the period 1995-2019. Therefore, we reject our first hypothesis 1*a)*. Dividing our test sample into January/non-January intervals, our results, however, indicate a significant SMB in January, which makes us accept our hypothesis 1*b)*. The results of our tests can be seen summarized in **Table 2** below**.**

A plausible alternative explanation for our *hypothesis 1a)* test result is that the effect in January and non-January are opposites which cancel each other out. For example, we find for months February-December, a statistically significant SMB factor (t-statistic –3.42) of a mean monthly SMB return of –0.68% between 1995-2019. Similarly, we see a statistically significant SMB effect in January, at +3.25% (t-statistic 3.46) on average. Since we find a small negative monthly return in February to December, and a much larger positive monthly return in January, these SMB effects could cancel out on average.

Overall, we find that Sweden has no statistically significant difference between the returns of small and big firms on average between 1995-2019. We believe the absence of SMB in Sweden, as compared to the United States (Asness et al., 2018a), could be due to the following reasons:

a) two opposing forces in SMB which cancel each other out, or
b) a diminishment of Swedish SMB in Sweden having occurred before 1995, or

[19] Please see appendix section 3 to see the results of factor robustness checks.

c) systematic differences between the two markets resulting in a weaker effect in Sweden, or
d) a combination of the above or other factors.

Table 2: Observed Small Minus Big (SMB) factor returns between 1995-2019

		SMB		
Sample	Years	Mean	Standard deviation	t-statistic
Longest sample	1995-2019	-0.35%	3.58%	-1.69
January	-	3.25%	4.69%	3.46
February-December	-	-0.68%	3.28%	-3.42

Table 2. Describes the "Small minus big" (SMB) factor's monthly returns in Sweden between 1995-2019, as well as the factor's monthly return in different subsets of our sample.

4.3.2 SMB Regression in Sweden

Proceeding to test the size effect in Sweden, through regressing SMB against other factors, we hypothesize that *2a) when adding well-known return factors our regression will better explain how SMB arises* (increasing adjusted R-squared). Furthermore, we hypothesize that *2b) when adding QMJ as an explanatory variable, we will have a positive increase in SMB alpha*. We expect this positive increase based on Asness et al. (2018a) seeing an increase of Swedish SMB alpha of +0.10% in their empirical robustness check on 23 international markets.

In **Table 3,** we regress SMB against the market factor and then stepwise add factors from our model to the regression. For each factor added (MKT, Lagging MKT, HML, UMD, QMJ), the regression's adjusted R-squared value increases, confirming *hypothesis 2a).* Furthermore, in the two final regressions (with the difference being QMJ), we can see that by including QMJ as a variable, SMB alpha increases by +0.11% to a non-significant SMB alpha mean of –0.03% (t-statistic –0.14) per month. This finding, therefore, also confirms our *hypothesis 2b) that adding QMJ increases SMB alpha.* However, throughout all our regressions, we find that SMB alpha is not statistically significant (with our final t-statistic at –0.14). Interpreting the non-significant SMB alpha, we find that there is no size effect in the Swedish equity markets between 1995-2019 when controlling for the above factors.

In addition to the above findings, we also find that all our explanatory factors are statistically significant in explaining SMB except for UMD. Furthermore, all the explanatory variables have negative coefficients, except for our lagging market excess return factor, meaning small firms have on average:

a) lower systematic risk exposure (market beta) than big firms,
b) longer price discovery periods in response to market-impacting macroeconomic news,
c) higher likelihood of being classified as "growth" compared to big firms,
d) no significant difference in momentum magnitude relative to big firms, and
e) higher likelihood of being classified as "junk" versus big firms.

Comparing the explanatory power of our regression to the regression of Asness et al. (2018a), we find that adding the QMJ factor to our regression raises adjusted R-squared relatively less than adding QMJ in the United States. In the United States, the model of Asness et al. (2018a) has an R-squared of 0.37 when including QMJ, whereas our adjusted R-squared with QMJ is 0.25. This result indicates that controlling for quality seems less important for SMB in Sweden than in the United States and suggests further factors could be appropriate to explain SMB in Sweden. Interestingly, our Carhart four-factor model with lagging market returns shows stronger explanatory power relative to their regression using the same factors, with our R-squared at 0.21 versus theirs at 0.15.

Table 3: SMB regression against Carhart and QMJ factors between 1995-2019

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

Sample	α	t(α)	β	t(β)	β-1	t(β-1)	h	t(h)	m	t(m)	q	t(q)	Adjusted R^2
Sweden 1995-2019	-0.21%	-1.05	-0.22	-5.93									10.24%
Sweden 1995-2019	-0.31%	-1.63	-0.24	-6.74	0.19	5.21							17.49%
Sweden 1995-2019	-0.26%	-1.38	-0.24	-6.93	0.19	5.36	-0.15	-3.33					20.20%
Sweden 1995-2019	-0.14%	-0.70	-0.27	-7.27	0.19	5.51	-0.20	-3.93	-0.07	-2.07			21.07%
Sweden 1995-2019	-0.03%	-0.14	-0.29	-8.04	0.19	5.58	-0.22	-4.48	-0.03	-0.95	-0.19	-3.89	24.68%

Table 3. Describes the coefficients and explanatory power of regressing SMB against the Carhart four-factor model, a lagging excess market return factor, and a QMJ factor between 1995-2019.

4.3.3 Swedish SMB alpha compared to the United States

Comparing our non-significant Swedish SMB alpha, of –0.03% per month (t-statistic –0.14), with Asness et al. (2018a) results in the United States of alpha +0.49% (t-statistic 4.89) in **Figure 1,** we find the increase in SMB alpha and SMB alpha overall being larger in the United States. Relative to the increase in SMB alpha of Asness et al. (2018a) in Sweden with QMJ (+0.10%), and our increase (+0.11%), we find our results differ by +0.01%. We believe this minor difference is because of differences in our respective sampling periods.[20]

Interpreting the absence of a significant size effect in Sweden, as compared to the United States, we believe the non-significant effect could be due to a range of potential reasons, including that:

a) there is no size effect in Sweden, due to differences in the equity markets of Sweden and the United States, or
b) the QMJ factor was constructed for the United States stock market, and has not been adequately adapted to the Swedish market, or
c) empirical errors, including potential bias in data, or
d) a combination of the above or other factors.

[20] Asness et al. (2018a) use a sampling period of 1983-2012 for calculating the Swedish increase in SMB alpha, whereas we use the period 1995-2019.

Figure 1: Comparison of SMB Alpha between the United States (1957-2012) and Sweden (1995-2019)

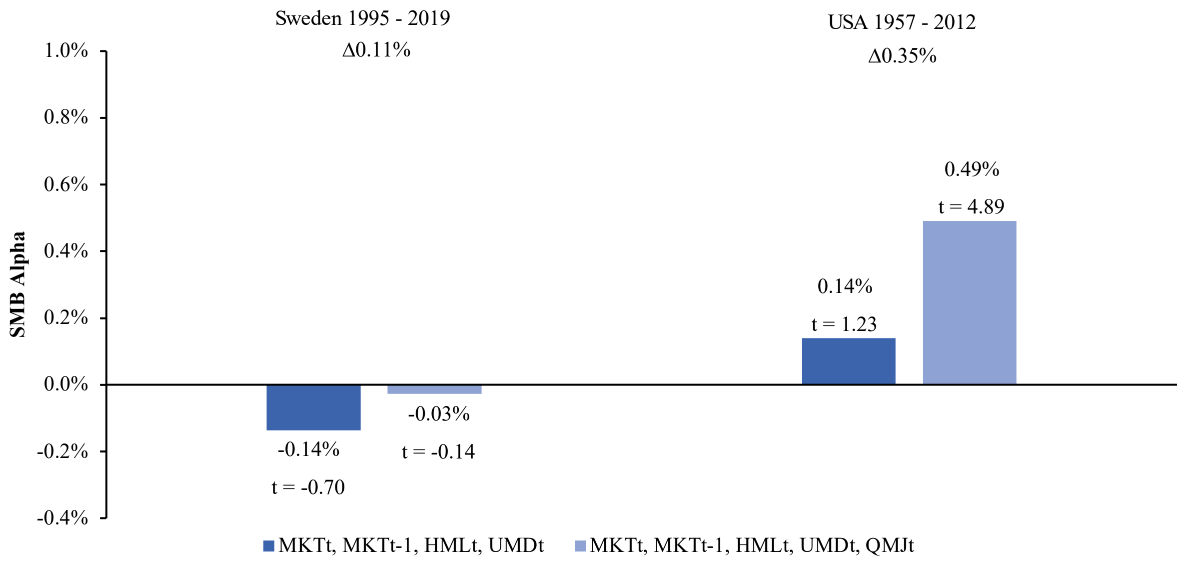

Figure 1. The figure describes SMB alpha results with and without controlling for QMJ, in Sweden and in the United States, as well as the change in SMB alpha after controlling for QMJ. The data on the United States come from Asness et al. (2018a).

4.3.4 SMB and QMJ in Sweden over time

Following our finding that controlling for quality results in a non-significant positive increase in SMB alpha, we dissect this interaction and look at how the relation between quality and size has developed over time. In plotting the various factors, we do not test for statistical significance as previously, but instead inspect visually. By examining **Figure 2** this way, we identify general trends in the interaction of our factors over time.

In **Panel 2A**, we plot 5-year moving averages of SMB alpha, SMB's beta on QMJ ("$Beta_{SMB\text{-}QMJ}$") multiplied by QMJ, and SMB. First, we see that SMB alpha has periodically taken on both negative and positive values during the period 1995-2019, which is in line with the on average non-significant SMB alpha in our regression. Furthermore, we see that when SMB alpha changes sign, this tends to coincide with QMJ × $Beta_{SMB\text{-}QMJ}$ changing sign. For example, when QMJ × $Beta_{SMB\text{-}QMJ}$ crosses the horizontal axis from positive to negative, SMB alpha tends to cross the horizontal axis from the opposite direction. This example indicates that time variation in QMJ × $Beta_{SMB\text{-}QMJ}$ is a strong determinant of the time variation in the sign of SMB alpha. This pattern has occurred for every observed change in the sign of QMJ × $Beta_{SMB\text{-}QMJ}$.

Examining the impact of QMJ on the size effect over time, we see that QMJ affects the size effect in three ways: the magnitude of QMJ, the sign of $Beta_{SMB\text{-}QMJ}$, and the magnitude of $Beta_{SMB\text{-}QMJ}$. We plot time series of QMJ, $Beta_{SMB\text{-}QMJ}$, and QMJ × $Beta_{SMB\text{-}QMJ}$ in **Panel 2B,** and find that our quality premium is consistently positive throughout the measurement period. Therefore, changes in the sign of QMJ × $Beta_{SMB\text{-}QMJ}$ result from a change in the sign of $Beta_{SMB-QMJ}$. Assuming consistently positive QMJ returns, a negative beta value can be interpreted as a higher concentration of quality among big firms than small firms, while a positive beta indicates an opposite effect. Comparing our $Beta_{SMB-QMJ}$ to the results of Asness et al. (2018a), they, by contrast, find a consistently negative beta in the United States. Therefore, size seems to more reliably predict quality over time in the United States than in Sweden.

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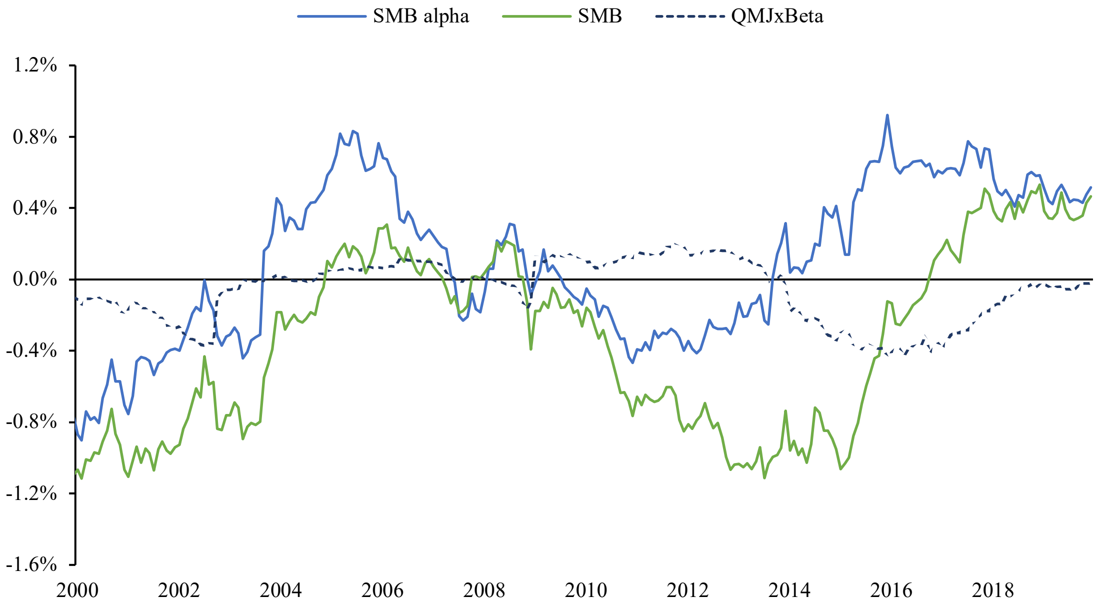
Figure 2: SMB, QMJ, and their interaction over time

Panel 2A: Five-year moving averages of SMB alpha, SMB and QMJ × Beta$_{SMB\text{-}QMJ}$



Panel 2B: Five-year moving averages of Beta$_{SMB\text{-}QMJ}$, QMJ, and Beta$_{SMB\text{-}QMJ}$ × QMJ

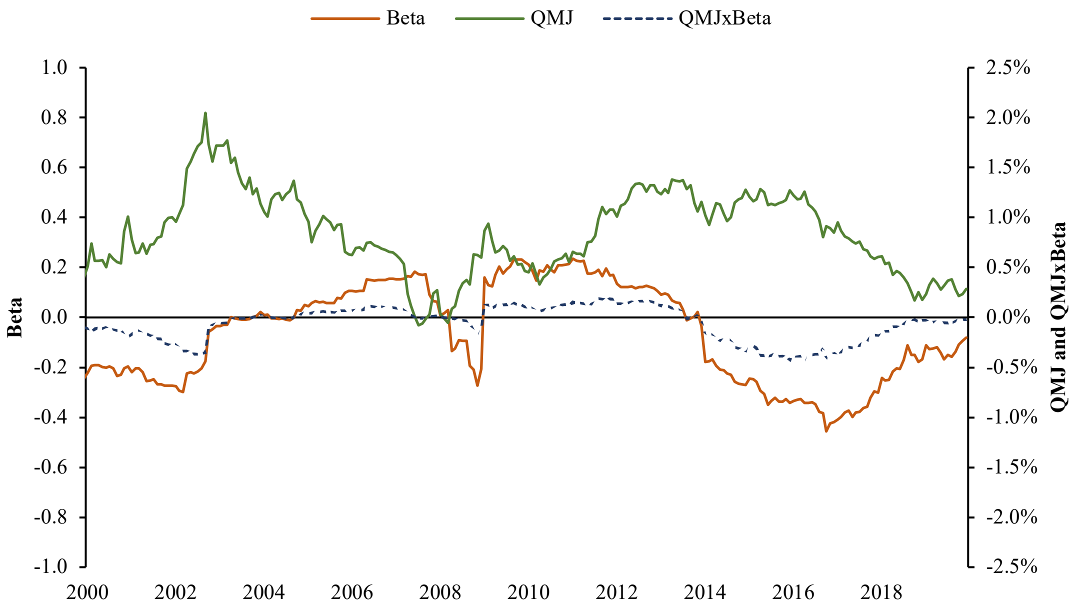


Figure 2. The figure's graphs describe the time series of SMB, SMB alpha, QMJ, and the decomposition of the interaction between QMJ and SMB. SMB alpha is calculated using our primary regression over rolling 5-year windows. Here, we calculate SMB as the average of rolling 5-year periods of our SMB factor using the zero-investment portfolio method. Beta between SMB and QMJ follows the same pattern and is calculated for rolling 5-year windows. Since we calculate our factors for the period 1995-2019, our use of calculations based on 5-year windows limits the plotted period to 2000-2019.

4.3.5 Size and quality in Sweden

Following the results of Asness et al. (2018a) that size and quality are positively correlated, we hypothesize that the same pattern can be observed in Sweden. Since we observe a quality premium throughout our measurement period and controlling for quality yields an inverse relation between alpha increase and size decile (Fig. 4), we expect a positive relationship between size and quality.

To further investigate this hypothesis, we graph time series with quality distributions among the smallest and biggest firms and size distributions among the firms of the highest and lowest quality. In **Figure 3**, we see these time series distributions among the top and bottom 20% of firms by size and quality. **Panel 3A** shows that small firms are predominantly junky and rarely reside in the top-quality decile. In **panel 3B,** we see that the largest firms are rarely junky, and quality is more common among big firms than small firms. This pattern is similar to the one observed in the United States by Asness et al. (2018a).

Panel 3C and 3D are the inverse plots of panels 3A and 3B. Panel 3C shows that the junkiest firms are predominantly small and rarely big, and panel 3D shows that quality firms are rarely small. Furthermore, panel 3D shows that quality firms are relatively evenly distributed among the top four size deciles. Comparing our high-quality firms' plots to the corresponding plots of Asness et al. (2018a), we see a tilt towards small firms in the United States, which is surprising given a positive relationship between size and quality. This difference indicates that firms in the top quality-decile are more likely to be among the largest firms in Sweden than in the United States.

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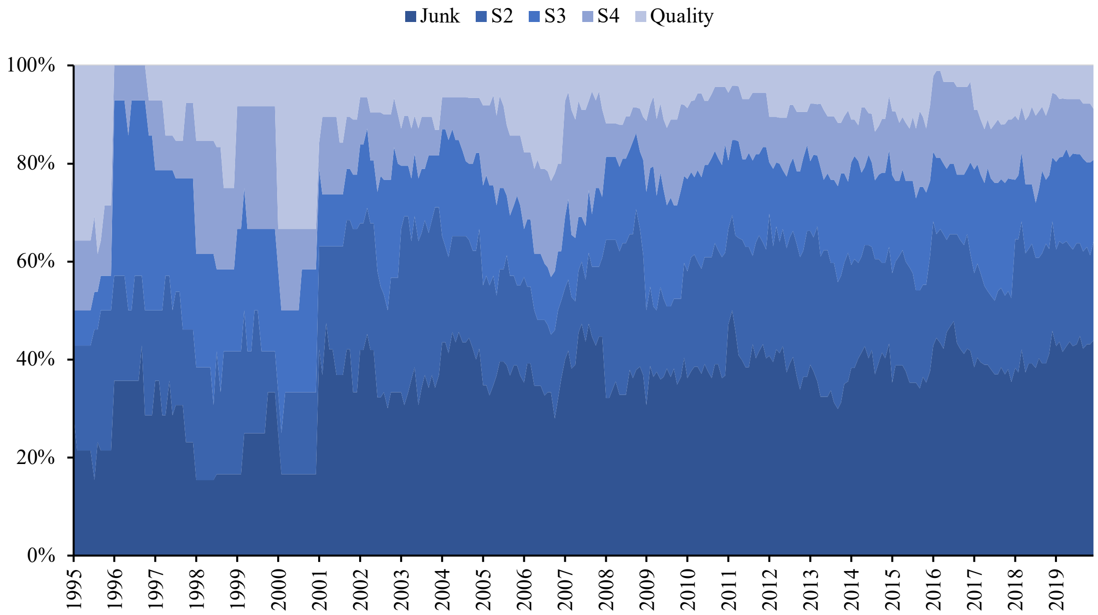
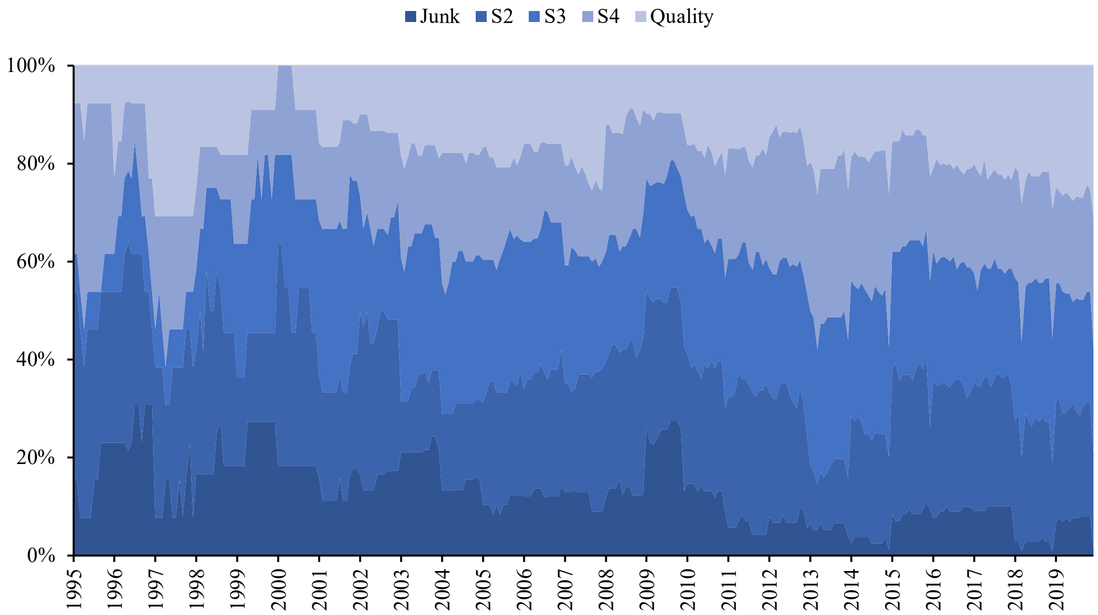
Figure 3: Distribution of quality across size decile

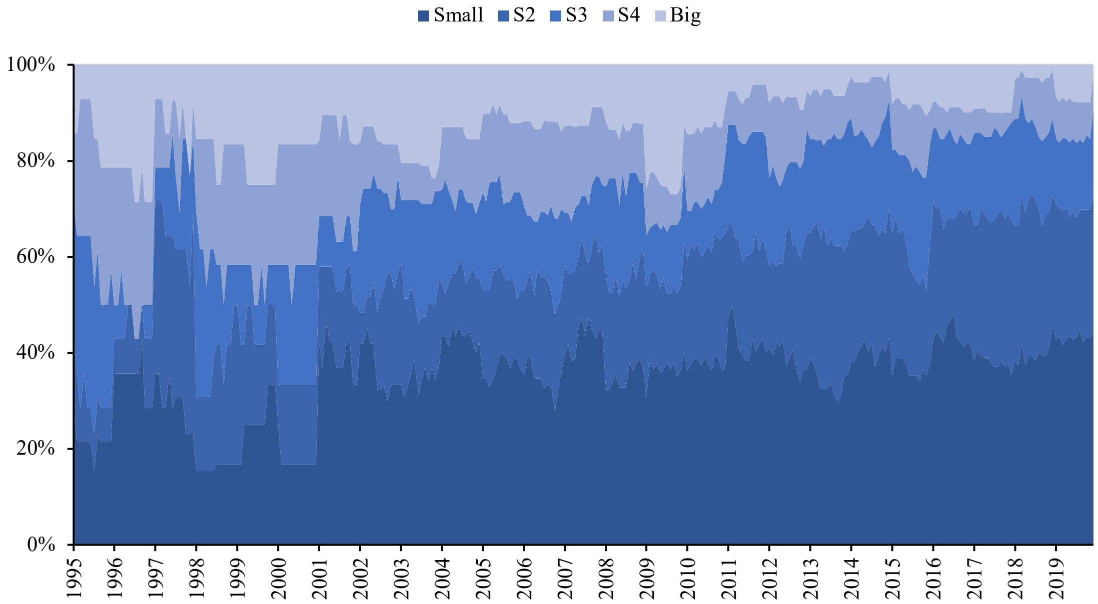
Panel 3A: Quality distribution among the smallest firms



Panel 3B: Quality distribution among the biggest firms



Panel 3C: Size distribution among low-quality (junk) firms



Panel 3D: Size distribution among high-quality firms

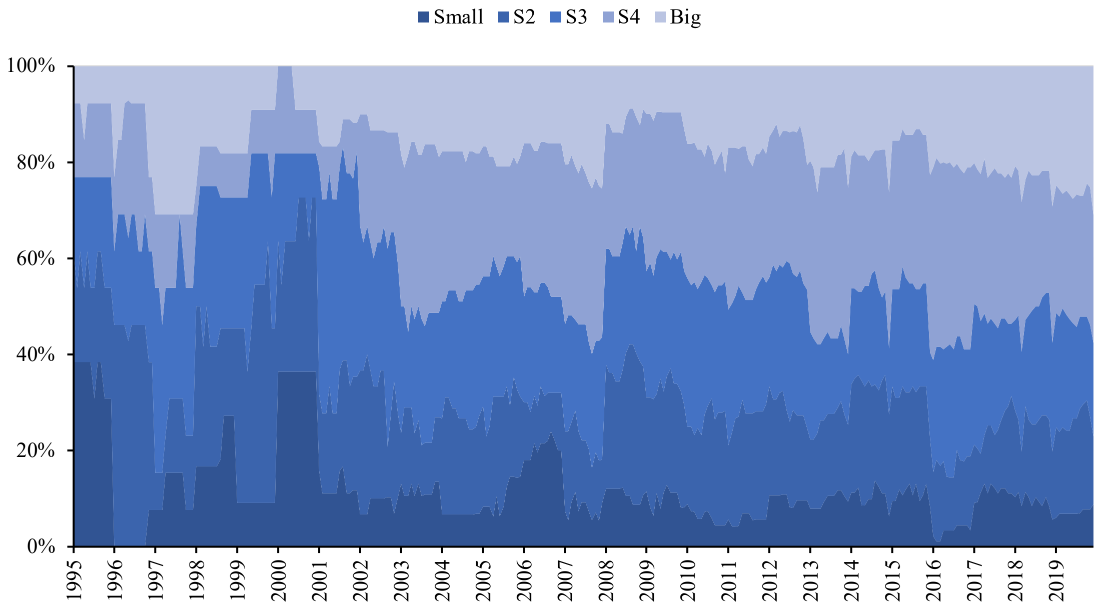


Figure 3. Panel A and B show distribution of quality over five quality quintiles (Junk, Q2, Q3, Q4, and Quality) among the top and bottom 20% of firms by size. Panel C and D show distribution of size over five size quintiles (Small, S2, S3, S4, Big) among the top and bottom 20% of firms by quality.

4.3.6 Alpha across size deciles

Having examined quality's relationship to size, we proceed to test the distribution of returns alpha across firm size deciles, hypothesizing that *6a) smaller firms will see a larger returns alpha increase when adding QMJ than bigger firms.* We expect this decreasing trend with increasing size because of our earlier results of quality's positive relationship with size, as well as based on Asness et al. (2018a) who found such a result in the United States. Furthermore, we hypothesize that *6b) the above trend will be linear (alpha increase becoming smaller with every size decile)*. We expect this linear trend, assuming that quality is not concentrated among extreme observations, as the increase in alpha controlling for quality should decrease as firms get bigger and have higher quality.

In Figure 4, we test the increase in returns alpha when adding QMJ to regressions of our model, sorting firms by their size deciles. We find non-significant increases in return alpha of +0.28% for firms in decile one and of –0.01% for firms in decile 10. Therefore, we find support for our *hypothesis 6a)*, as the increase in alpha appears to become smaller as firm size increases. We also find that the increases in alpha appear weakly linearly distributed across the size deciles, which supports *hypothesis 6b)*. This indicates a general linear positive relation between size and quality, and that quality differences are not concentrated among extreme observations.

Figure 4: Differences between returns alpha increase with QMJ across size deciles

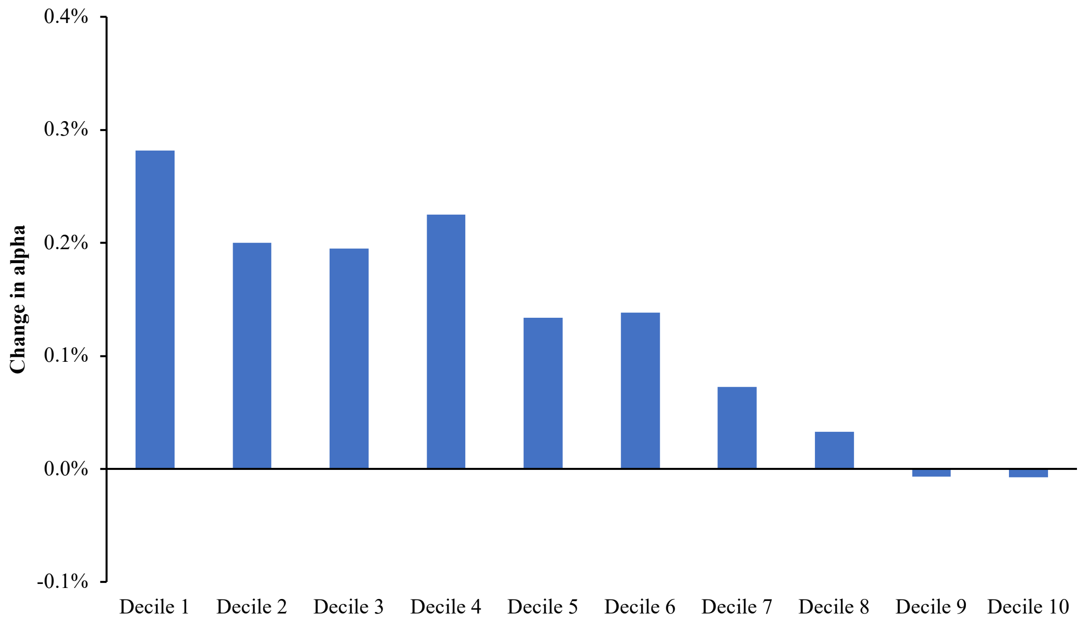


Figure 4. The graph illustrates the increase in monthly returns alpha when including the QMJ factor. Every month, we create ten value-weighted portfolios – one for each size decile of firms. We regress each portfolio's returns on MKT, MKT lagged one month, UMD and HML. We then add QMJ to the regression and observe the change in the regressions' alpha values.

5. Conclusion and limitations

Following our tests, we find that the SMB factor is not significant in Sweden on average between 1995-2019. Examining SMB controlling for the month of January, however, we find a statistically significant SMB with positive mean in January and negative mean in February-December. Combined, these two opposing effects on SMB offer an alternative explanation to SMB being non-significant / zero on average. When regressing our SMB factor against Carhart's four-factor model and lagging market returns, we find non-significant SMB alpha, indicating the lack of a size effect without controlling for quality.

Controlling for quality through QMJ, we find that QMJ is statistically significant in explaining SMB and consistently increases SMB alpha. However, adding QMJ to our regression brings SMB's alpha from a non-significant negative value to an even less significant value, in support of no size effect in Sweden.

Examining the impact of controlling for quality in monthly returns alpha across different size deciles, we find a general increase in returns alpha that decreases linearly with size. These results are in line with the negative coefficient of QMJ and indicate a positive relationship between size and quality in Sweden. Furthermore, we also find that smaller firms on average being junkier explains most of the observed negative, yet non-significant, size effect in Sweden. Looking closer at the interaction between size and quality, we find a consistent quality premium in Sweden. Despite this, we find that the correlation between size and quality has varied over time, with SMB's beta on QMJ periodically becoming positive, although generally being negative. This generally negative beta is in line with QMJ's inclusion in the regression increasing SMB alpha on average and justifies controlling for quality when testing the size effect.

Overall, we find that there is no size effect, positive or negative, in Sweden between 1995-2019 when controlling for quality and our other return factors. We believe the consistent quality premium and a generally positive relationship between size and quality, have previously obscured the lack of a relation between size and returns in Sweden. We suggest further research to include why a quality premium exists in Sweden, why its correlated to size, and how this relation has altered time. Additionally, we also suggest exploring other factors potentially explaining SMB in Sweden, for example, a liquidity factor.

5.1 Limitations

We see a few possible limitations to our tests, and our results should be viewed in light of these. For example, the slight heteroscedasticity in our derived factors, a potential bias in Compustat's data sampling, and the relatively low increase in adjusted R-squared when including the QMJ factor. We have tried to reduce the impact of these limitations by recreating all factors from the ground up, removing as few observations as possible, and adapting the QMJ factor using Swedish classifications. However, to take our results even further, we advise to use a broader data sample in the number of firms and time period, which would decrease the impact of outliers and increase statistical significance.[21]

[21] As we use all available data from Compustat Capital IQ as accessed on 31/03/2020, we would suggest using another database or combining multiple databases in a possible extension.

6. References

6.1 Published papers

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Appendix

A.1 Empirical data sampling and processing

This section describes how we process data in the empirical study, which observations we drop and the number of observations at the various stages of the analysis. Initially, we took all our accounting and market data from the Compustat Capital IQ database, sourcing all data points for country code "SWE" between 1987-06 to 2020-03.

A.1.1 Fundamentals data

From 13 246 to 12 664 observations

	# of observations
Original sample (1987-2019)	13 246
Drop duplicate observations, keep most recent accounting data by June	– 64
Drop if fiscal year < 1995 due to limited sample size	– 518
Final sample (1995-2019)	**12 664**

A.1.2 Market data

From 3 233 781 to 115 322 observations

	# of observations
Original sample (1985-2019)	3 233 781
Drop if observations are not common shares	– 76 597
Drop if shares do not have a claim on the company's earnings	– 361 042
Drop if price observation is not at month-end (after calculating daily beta)	– 2 656 355
Drop if the share class is not the primary share class of company	– 19 173
Drop if fiscal year < 1995 due to limited sample size	– 5 290
Drop if extreme monthly return (over 1000%)	– 3
Final sample (1995-2019)	**115 322**

A.2 Construction of QMJ quality metrics

This section describes the calculations of the various quality metrics used to determine our QMJ subset portfolios. For metrics which use accounting data only, we update metrics on an annual basis. For metrics that include both accounting and market data, metrics we update metrics on a monthly basis.

A.2.1 Profitability metrics

GPOA = Gross profits over assets =
$$(Revenue\ -\ COGS)\ \div\ (Total\ assets)$$

ROE = Return on equity =
$$(Net\ income) \div (Shareholders\ equity)$$

ROA = Return on assets =
$$(Net\ income) \div (Total\ assets)$$

where *shareholders equity* is equity attributable to parent, excluding minority interest

CFOA = Cash flow over assets =
$$(Free\ cash\ flow) \div (Total\ assets)$$

where free cash flow is calculated as follows:
$FCF = (Net\ income\ +\ Depreciation\ -\ \Delta\ Working\ capital\ -\ Capex)$ and
$\Delta\ Working\ capital = (Working\ capital)_t - (Working\ capital)_{t-1}$

GMAR = Gross margin =
$$(Revenue\ -\ COGS)\ \div\ (Revenue)$$

LACC = Low accruals =
$$-(\Delta\ Working\ capital\ \ -Depreciation)\ \div\ (Total\ assets)$$

A.2.2 Growth metrics

G_GPOA = Growth in gross profits over assets across this year and 4 years prior=
$$((Revenue\ -\ COGS)_t - (Revenue\ -\ COGS)_{t-4}\ )\ \div\ (Total\ assets)_{t-4}$$

G_ROE = Growth in return on equity across this year and 4 years prior =
$$((Net\ income)_t - (Net\ income)_{t-4}\ ) \div (Shareholders\ equity)_{t-4}$$

G_ROA = Growth in return on assets across this year and 4 years prior =
$$((Net\ income)_t - (Net\ income)_{t-4}\ ) \div (Total\ assets)_{t-4}$$

G_CFOA = Growth in cash flow over assets across this year and 4 years prior =
$$(-(\Delta\ Working\ capital - Depreciation)_t - (-(\Delta\ Working\ capital - Depreciation))_{t-4}\ ) \div (Total\ assets)_{t-4}$$

G_GMAR = Growth in gross margin across across this year and 4 years prior =
$$((Revenue\ -\ COGS)_t - (Revenue\ -\ COGS)_{t-4}\ )\ \div\ (Revenue)_{t-4}$$

G_LACC = Growth in low accruals across across this year and 4 years prior =
$$((Revenue\ -\ COGS)_t - (Revenue\ -\ COGS)_{t-4}\ )\ \div\ (Revenue)_{t-4}$$

A.2.3 Safety metrics

LEV = Low leverage =
$$-(Long\ term\ debt\ + Short\ term\ debt + Minority\ interest\ + Preferred\ stock) \div (Total\ assets)$$

BAB = Betting against beta =
$$-beta = -(Correlation\ _{stock\ i, OMXSPI\ index}) \times (\sigma_{stock\ i}\ \div\ \sigma_{OMXSPI\ index})$$

where $Correlation_{stock\ i, OMXSPI\ index}$ is calculated from daily returns for the past rolling three years and the standard deviation is calculated from daily returns for a rolling period of the past one year

Altman Z score =
$$(1.2 \times Working\ capital\ +\ 1.4 \times Retained\ earnings\ +\ 3.3 \times EBIT\ + 0.6 \times Market\ capitalization\ +\ Revenue)\ \div\ (Total\ assets)$$

where *Market Capitalization* is calculated as *(shares outstanding* × *share price)* for all type of equity securities available for a single firm in our data sample per month

EVOL = Standard deviation of return on equity over rolling past five years =
$$\sigma\ _{ROE\ over\ the\ past\ five\ years}$$

A.3 Robustness check: Our derived factors compared to SHOF's factors

In order for us to conduct our analysis to its full extent, we choose to calculate our model's monthly return factors from the ground up. These calculations are an extensive process, and the derived factors are central to our study. We have therefore compared our derived factors to the ones available for the Swedish market published by the Swedish House of Finance (SHOF) as a robustness check. In doing this, we investigate the reliability of our calculations. As seen in **figure 5 below,** we find that all of our factors generally move in conjunction with those of SHOF, but that SHOF's factors sometimes take on very large values, which our's do not. From visual inspection, we consider it likely that our calculations are robust and correct. Differences in individual months do not necessarily indicate that either our or SHOF's factors are incorrect. It is likely the result of differences in the methodology used.

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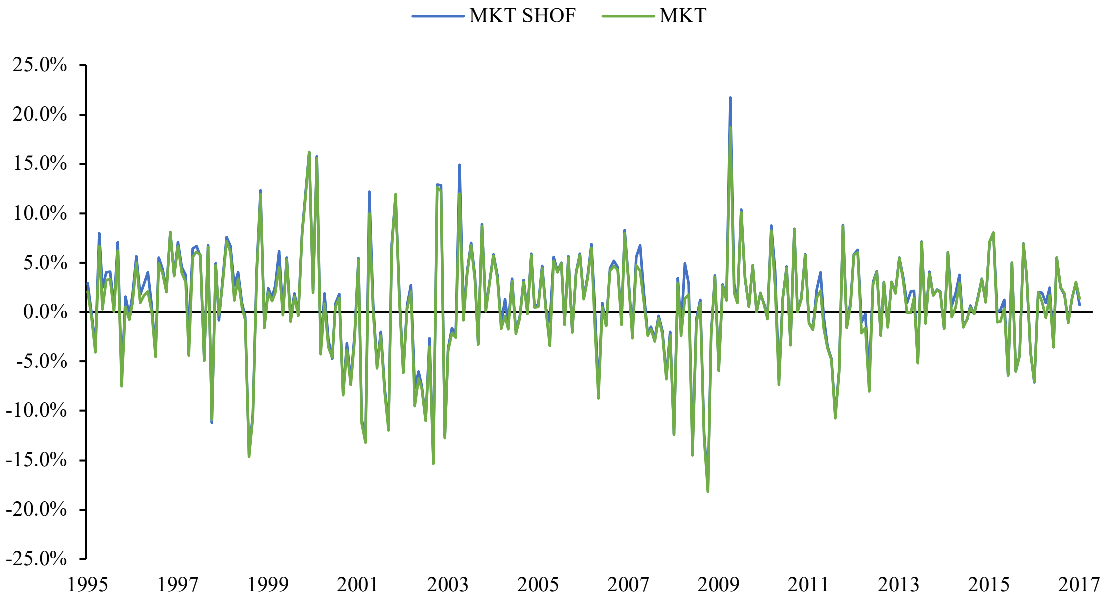
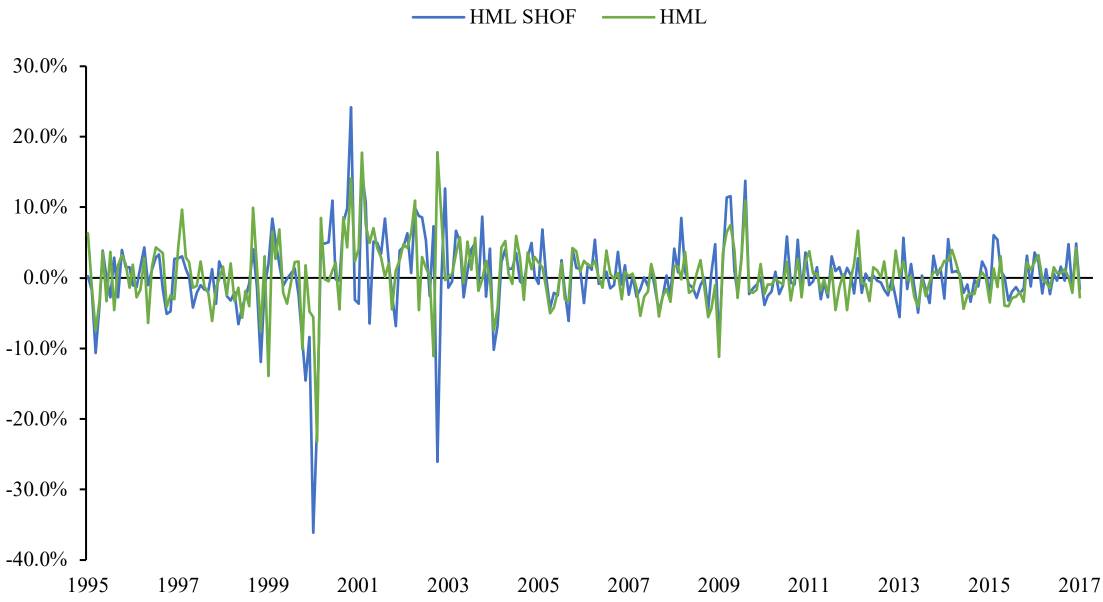
Figure 5: Comparison of our factors to Swedish House of Finance's factors

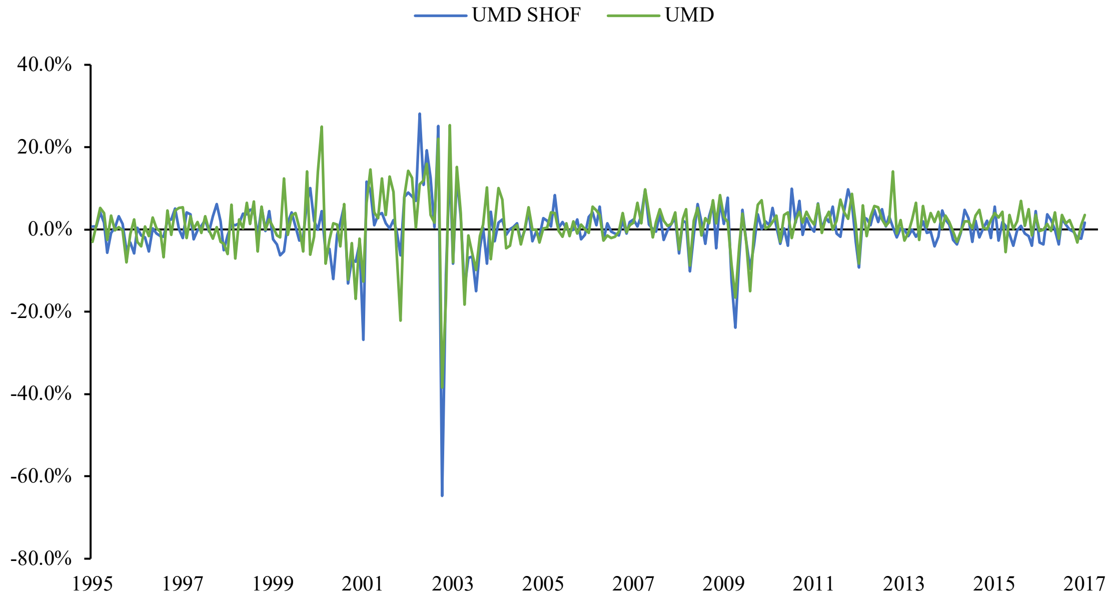
Panel 5A: Times series of our and SHOF's MKT factor for the Swedish stock market



Panel 5B: Times series of our and SHOF's HML factor for the Swedish stock market



Panel 5C: Times series of our and SHOF's UMD factor for the Swedish stock market



Panel 5D: Times series of our and SHOF's SMB factor for the Swedish stock market

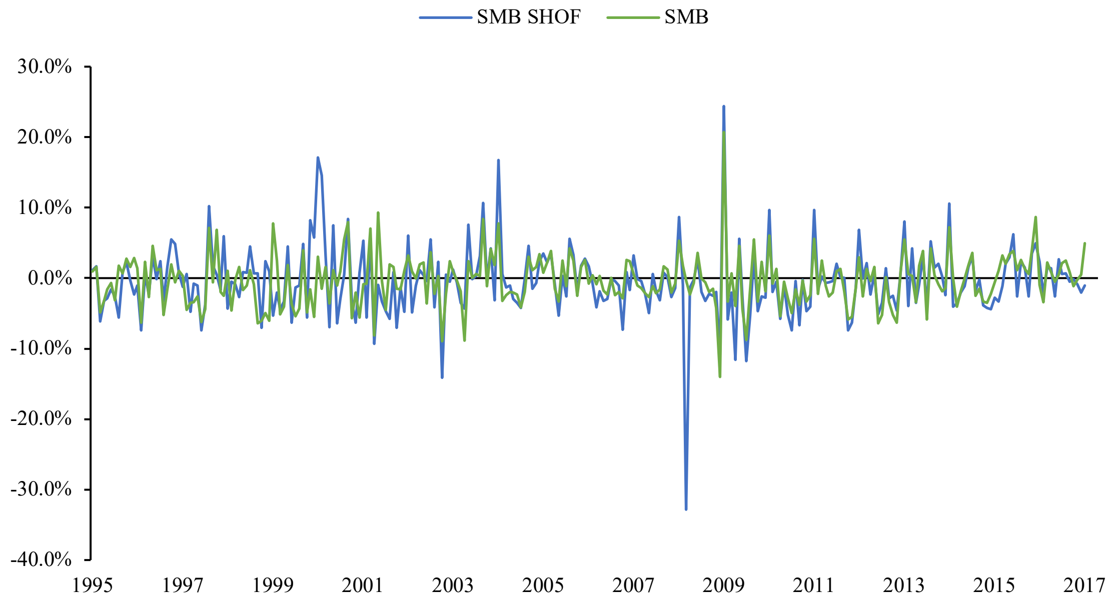


Figure 5. The figure shows plots of times series of our calculated factors versus the same factors calculated by the Swedish House of Finance. The period 1995-2017 is the complete overlap of available data on our factors and those of the Swedish House of Finance.

A.4 Robustness check: Tests for multicollinearity, homoscedasticity, autocorrelation

Since we conduct an ordinary least squares regression, we test for multicollinearity, homoscedasticity and autocorrelation to evaluate the validity of our model. We find that our regression exhibits some homoscedasticity, no multicollinearity and no autocorrelation.

A.4.1 Test for multicollinearity in factors

Computing variance inflation factors, as seen in **table 4**, we find that our regression does not exhibit an issue with multicollinearity.

Table 4: Test for multicollinearity

	Without QMJ		With QMJ	
Variable	**VIF**	**1/VIF**	**VIF**	**1/VIF**
UMD	1.42	0.71	1.54	0.65
HML	1.31	0.77	1.33	0.75
MKT	1.14	0.88	1.27	0.79
MKTt-1	1.02	0.98	1.18	0.85
QMJ	-	-	1.02	0.98
Mean VIF	1.22		1.27	

Table 4. The table illustrates variance inflation factors from our SMB regression with and without QMJ.

A.4.2 Test for homoscedasticity in factors

Visual inspection from plotting our error terms against our model's fitted values indicates growing dispersion in error terms, hinting at a problem with heteroscedasticity, as seen in **figure 6 below**.

Figure 6: Residuals versus fitted values for primary regression

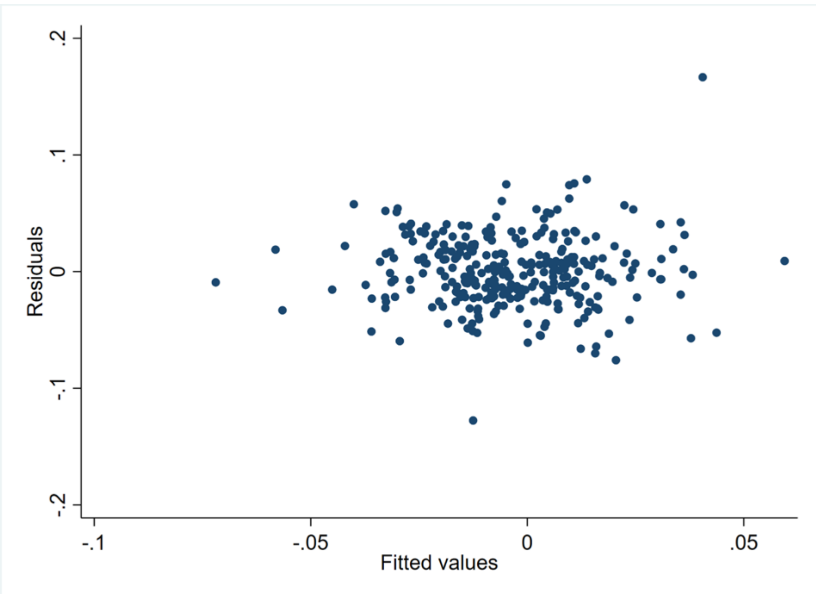


Figure 6. The graph illustrates our residuals versus our fitted values for our primary regression including QMJ.

White's test for homoscedasticity in **Table 5** confirms that heteroscedasticity is present. The heteroscedasticity could stem from a model specification error. In our model, we assume a linear relationship between SMB and the exogenous variables, but the relationship could be of any other form. We do not find any significant relationships between our error terms and any of our exogenous variables. Running logarithmic regressions between SMB and the exogenous variables, we find no logarithmic relationships.

We consider the omission of important variables an unlikely cause of heteroscedasticity since our variable selection follows the method of Asness et al. (2018). Lastly, it could stem from data and data processing errors, i.e. large observed outlier SMB values are the result of an error. For some points in time, factors consist of only a small number of firms, and any extreme returns can disturb the SMB factor. This likely contributes to the heteroscedasticity since some observations of SMB are larger than can be reasonably expected.

Table 5: White's test for heteroscedasticity

	Without QMJ			With QMJ		
Source	**chi2**	**df**	**p**	**chi2**	**df**	**p**
Heteroscedasticity	46.4	14	0.00	50.1	20	0.00

Table 5. The table illustrates our test for heteroscedasticity using a White's test.

A.4.3 Test for autocorrelation in factors

We conduct a Breusch-Godfrey test for autocorrelation and find that our regressions do not exhibit autocorrelation, as seen in **table 6** below.

Table 6: Breusch-Godfrey test for Autocorrelation

QMJ	lag	chi2	df	Prob > chi2
Excluded	1	1.74	1	0.19
Included	1	1.47	1	0.23

H0: no serial correlation

Table 6. The table illustrates a Breusch-Godfrey test for autocorrelation both with and without including QMJ. We set lag to one, following conventional procedure.