Idiosyncratic Volatility and Risk-Adjusted Returns: Evidence from the Swedish Stock Market

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ABSTRACT

Classic financial theory says that an investor should not be compensated for holding diversifiable risk, and that no relation between diversifiable risk and returns should exist. However, research has shown diversifiable risk, or idiosyncratic volatility, to be both positively and negatively related to returns, depending on the application. The purpose of this thesis is to examine the relation between idiosyncratic volatility and returns in the Swedish stock market. Using a sample consistently containing nearly all Swedish listed stocks from July, 1994, through December, 2013, and measuring idiosyncratic volatility relative to the Fama-French three-factor model, we show that there is a significant negative relation between idiosyncratic volatility and risk-adjusted returns in the Swedish stock market between February and December months. Additionally, we show that when the smallest stocks are excluded, there is a negative relation between idiosyncratic volatility and risk-adjusted returns in the Swedish stock market throughout the year.

Keywords: Idiosyncratic volatility, Fama-French three-factor model, Risk-adjusted returns, January effect, Microcap stocks

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Table of contents

1 Introduction

There is a widely accepted relationship between risk and return, the risk-return tradeoff, where investments with higher risk are associated with higher expected returns and investments with lower risk are associated with lower expected returns. Further, the capital asset pricing model (CAPM) says that investors are only rewarded for holding systematic risk. Through diversification, investors can mitigate idiosyncratic (firm-specific) risk, why holding this risk should not be rewarding. Under the assumptions of the CAPM, there should consequently be no additional gains from holding idiosyncratic risk, suggesting that the relationship between idiosyncratic risk and returns is non-existent.

Previous research has shown that the assumptions of the CAPM typically do not hold, providing us with a possibility that the relation between idiosyncratic risk and returns is different from zero.[1] The general idea has been that by taking on more idiosyncratic risk, and thereby more risk overall, an investor should be positively compensated in terms of returns. This notion of a positive relation between idiosyncratic volatility and returns was heavily challenged in 2006, when Ang, Hodrick, Xing, and Zhang (henceforth Ang et al.) published a paper suggesting a *negative* relationship between idiosyncratic risk and returns for U.S. stocks. Following these findings, both confirmative and contradictive evidence has been presented. Thus, it appears there is no overall consensus regarding the relationship between idiosyncratic volatility and returns.

The purpose of this thesis is to examine the relationship between idiosyncratic risk and returns in the Swedish stock market and evaluate its robustness. By doing so we hope to achieve a better understanding of the relationship and gain insight into the factors affecting it. We are interested in the Swedish stock market, as we believe findings on the Swedish stock market can prove representative of other developed markets since previous research has found consistent results across developed

[1] Levy (1978) and Merton (1987) develop models based on the CAPM and show that idiosyncratic risk can be positively related to expected returns in a setting where investors hold undiversified portfolios and demand a premium for holding idiosyncratic risk.

markets.[2] Previous research on the relationship between idiosyncratic risk and returns focuses mainly on the U.S. or the G7 countries, why Sweden is also interesting for its relatively smaller market size. No previous study examining the relationship between idiosyncratic volatility has focused on the Swedish stock market specifically, and in the only previous study where Swedish stocks make up a large portion of the sample, all Swedish listed stocks are not included.[3]

Thus, this thesis contains two main contributions. First, our study serves a complement to previous research primarily focused on the U.S. or G7 countries, examining whether a relationship between idiosyncratic volatility and returns exists in the much smaller Swedish stock market when all listed stocks are included. Second, we employ methodologies that have given rise to conflicting results in previous research subsequent to Ang et al. (2006). This provides us with the opportunity to evaluate the robustness of previous findings and allows us to draw more specific conclusions about the relation between idiosyncratic volatility and returns in the Swedish stock market.

Our study is restricted to all Swedish listed stocks from July, 1994, through December, 2013. Following the methodology of Ang et al. (2006), we measure idiosyncratic volatility for each stock relative to the Fama-French three-factor model and sort stocks into quintile portfolios based on their level of idiosyncratic volatility. We then measure each portfolio's raw return over the next month, and to control for systematic factors, we risk-adjust the portfolio excess returns using the Fama-French three-factor model. Next, we examine the difference between the highest and lowest

[2]See for example Ang et al. (2009), Brockman, Schutte, and Yu (2009), and Guo and Savickas (2010).

[3]Ang et al. (2009) include Sweden (data until December, 2003) in their international dataset but report only summary statistics that are insufficient for drawing any conclusions about the relationship in the Swedish stock market. Brockman, Schutte, and Yu (2009) also include Sweden (data until October, 2007) in their international dataset but when implementing the same portfolio approach as Ang et al. (2006), they compute conditional, or expected, idiosyncratic volatility following an EGARCH approach instead of using lagged idiosyncratic volatility. Subsequent research has shown that conditional idiosyncratic volatility is biased. In their MSc thesis, Ask and McBeath (2012) confirm the base finding of Ang et al. (2006) for the Nordic equity markets as a whole but limit the Swedish portion of their sample to NASDAQ OMX stocks only, implying a size bias as stocks listed on the NASDAQ OMX lists are typically larger. Additionally, they do not perform any of the controls or alterations to the portfolio approach that are performed by Ang et al. (2006) or in subsequent research to assess the robustness of the negative relation. On a smaller note, they use log returns, which prevents full comparison of their findings to those of Ang et al. (2006) and other prominent papers on the subject.

idiosyncratic volatility portfolios. While Ang et al's (2006) methodology serves as our baseline framework, we extend the study to control for alternative research methods proposed by other studies that find conflicting, supportive, and/or more specific evidence on the relationship between idiosyncratic volatility and returns.

It has been argued that the results of Ang et al. (2006) are sensitive to the estimation of idiosyncratic volatility and the subsequent portfolio weighting approach. Conflicting results are documented when monthly data, as opposed to daily, is used for estimating idiosyncratic volatility, and also when portfolios are equal-weighted, as opposed to value-weighted (Bali and Cakici, 2008). In an attempt to understand the different results, and examine if the same holds for the Swedish stock market, we employ both different estimation periods and weighting schemes. We also control for a January effect documented in Peterson and Smedema (2011) and Chen et al. (2012) and a small stock effect documented in the latter.

Similar to Ang et al. (2006) in the U.S. market, we find a significant negative relationship between idiosyncratic volatility and risk-adjusted returns in the Swedish stock market. The negative relationship is robust to controlling for firm characteristics and market anomalies, altering the estimation periods and weighting schemes, excluding January months and microcaps, and using sub-samples. The negative relationship disappears when portfolios are equal-weighted but reemerges with the exclusion of microcaps and January months, respectively.

The remainder of the paper is structured as follows. Section 2 provides an overview of the previous research on the relation between idiosyncratic volatility and returns. Section 3 introduces the methodology employed and the data used in our study. Section 4 presents our findings with further analysis and interpretation. Section 5 concludes our main findings. Finally, Section 6 offers suggestions for future research.

2 Literature review

This section serves as an introduction to existing research on the relation between idiosyncratic volatility and returns. We begin by presenting the findings of Ang et al. (2006), which has served as our motivation and initial reference, and their succeeding paper, Ang et al. (2009). We then move on to provide an overview of papers finding a positive relation between idiosyncratic volatility and stock returns in subsection 2. Subsection 3 presents papers finding conflicting evidence on the relation, and subsection 4 concludes with studies finding a negative relation. Table 1, presented after subsection 4, summarizes the literature discussed.

2.1 The puzzling findings of Ang, Hodrick, Xing, and Zhang

As briefly mentioned in the Introduction section, previous empirical findings show no relation, or a positive relation, between idiosyncratic risk and expected return, which is in line with the CAPM and the risk-return tradeoff, respectively. Therefore, the findings of Ang et al. (2006), suggesting that U.S. stocks with high idiosyncratic volatility on average have lower returns, attracted a lot of attention when they were published. These findings were reinforced in their 2009 paper, extending the study to 23 developed countries.

By defining idiosyncratic volatility relative to the Fama and French (1993) three-factor model, Ang et al. (2006) show that stocks with higher idiosyncratic volatility earn lower average and risk-adjusted returns for U.S. stocks on the NYSE, NASDAQ, and AMEX from July, 1963, through December, 2000. According to the authors, their approach is different from earlier research in that they study idiosyncratic volatility at the firm level and sort stocks into value-weighted portfolios on this basis. To test the robustness of their findings, they perform a battery of tests to control for size, book-to-market, leverage, liquidity, volume, turnover, bid-ask spreads, coskewness, dispersion in analysts' forecasts, and momentum. Further, the findings are also robust to excluding NASDAQ and AMEX, which contain a large number of small stocks relative to the NYSE.

In the later paper, Ang et al. (2009) extend their study to 23 developed countries from the 1980s through December, 2003. For the U.S. they add an additional three years compared to their first study and perform further robustness tests. The negative relation is apparent and significant, although not as strong, for all non-U.S. G7 countries, as well as for larger samples where countries are pooled on either a regional or a global basis.[4] The relation is primarily examined using Fama-MacBeth regressions, which is different to Ang et al. (2006), and analogous to an equal-weighted portfolio approach. To control for equal weighting, they perform value-weighted Fama-MacBeth regressions, which yields an even stronger and more significant negative relation. Another potential concern is the estimation period used to compute idiosyncratic volatility. To control for this they extend their estimation period from one month to three, six, and twelve months, respectively. The coefficient on idiosyncratic volatility decreases as they move towards a longer formation period but remains negative and significant throughout the different periods. The three-month coefficient is actually slightly stronger compared to the one-month coefficient. The authors suggest more accurate estimates of volatility are obtained over three months compared to only one.

For the U.S. data they add additional controls in the form of transaction costs, degree of informed trading, analyst coverage, institutional ownership, price responsiveness to information, and coskewness. The results remain robust to all specifications with analyst coverage and price responsiveness being the two variables that reduce the negative relationship the most, although not to the extent that the relation is no longer negative and statistically significant. The authors also present evidence on a strong covariation between the low returns of high idiosyncratic volatility stocks in international markets and the U.S. analogy, suggesting that a U.S. idiosyncratic volatility factor is the primary driver behind the global idiosyncratic volatility effect.

[4] Ang et al. (2009) only report country-specific data for each G7 country (Canada, France, Germany, Italy, Japan, the UK, and the U.S.).

2.2 Literature on the positive relationship between idiosyncratic volatility and returns

Literature finding a positive relationship dates back to 1965 and shows continued support going forward.[5] We focus on more recent literature in connection to the findings of Ang et al. (2006) and onwards.

Fu (2009) questions the use of lagged idiosyncratic volatility in Ang et al. (2006) and argues that lagged idiosyncratic volatility is not a good proxy for expected idiosyncratic volatility. Instead, Fu uses the EGARCH model to estimate expected volatility and finds a positive relationship with returns. Further, Fu replicates the results of Ang et al. (2006) and argues that these are driven by the return reversal of stocks.[6] These findings are supported by the results in Huang et al. (2010), who also estimate conditional idiosyncratic volatility using the EGARCH methodology, and find a positive relationship and point to return reversals in explaining the results of Ang et al. (2006). Two other papers that adopt the EGARCH methodology are Eiling (2013) and Spiegel and Wang (2005). Eiling finds a positive premium for idiosyncratic risk, using both the CAPM and the Fama-French three-factor model. She explains parts of the positive premium with industry-specific human capital. Spiegel and Wang also look at liquidity as a determinant of stock returns but find a much stronger impact from idiosyncratic risk, confirming the positive correlation. Unlike the previously mentioned papers, Brockman, Schutte, and Yu (2009) use the EGARCH model to look at an international context, also to confirm the positive relation.

Chua, Goh, and Zhang (2010) on the other hand, decompose idiosyncratic risk into expected and unexpected volatility. They find that expected and unexpected volatility are positively correlated with expected and unexpected returns, respectively. The former is consistent with the studies above employing EGARCH. They use unexpected volatility to control for unexpected returns and argue that the exclusion of unexpected returns leads to the wrong conclusions. The fact that Ang et

[5]See for example Lintner (1965), Ticnic and West (1986), Lehmann (1990), King, Sentana, and Wadhwani (1994), Malkiel and Xu (1997, 2002).

[6]Fu (2009) argues that idiosyncratic volatility and returns are high simultaneously, with returns tending to reverse in the following month.

al. (2006, 2009) do not examine expected volatility and returns is mentioned as an important aspect.

2.3 Literature with conflicting evidence on the relationship between idiosyncratic volatility and returns

Bali and Cakici (2008) are able to replicate the findings of Ang et al. (2006) following a similar approach. Using the same portfolio weighting scheme as Ang et al. (2006), they also find a significant negative relation between idiosyncratic volatility and risk-adjusted returns using NYSE idiosyncratic volatility breakpoints or an equal market share approach to sort stocks into quintiles, instead of basing the idiosyncratic volatility breakpoints on quintiles of the entire sample, as done in Ang et al. (2006). When only looking at NYSE stocks as compared to NYSE, AMEX, and NASDAQ combined, the negative relationship is significant for the quintile breakpoint sorting approach used by Ang et al. (2006), but not for the equal market share approach.

When measuring idiosyncratic volatility differently, Bali and Cakici (2008) also find contradicting results. The use of monthly data (previous 24 to 60 monthly returns) to calculate idiosyncratic volatility yields no significant results when NYSE idiosyncratic volatility breakpoints are used to form quintile portfolios or when quintile portfolios are formed such that each quintile contains an equal proportion of the market (20%). However, when quintile portfolios are formed in the same manner as in Ang et al. (2006), Bali and Cakici (2008) find a significant negative difference in risk-adjusted returns between the quintile with highest idiosyncratic volatility and that with the lowest. The negative relation is lower in both magnitude and significance compared to the base case using daily returns to calculate idiosyncratic volatility.

When forming idiosyncratic volatility quintiles in the same manner as Ang et al. (2006), but employing equal weighting or inverse volatility weighting schemes instead of value weighting, they find no significant relationship. Using equal-weighted portfolios can be motivated by a wish to avoid a few big stocks driving the results

(Fama and French, 2008). Regarding the use of inverse volatility-weighted portfolios, Bali and Cakici (2008) argue that lower weights should be assigned to stocks with higher idiosyncratic volatility, since they are typically small, illiquid and low priced. As a final robustness check of the findings in Ang et al. (2006), they exclude the smallest, lowest priced and most illiquid stocks. This results in the disappearance of the significance found in Ang et al. (2006).

In a later paper, Bali, Cakici, and Whitelaw (2011) examine the relationship between the maximum daily return over the past month, "MAX", and expected returns. They find a negative and significant relation. They argue that idiosyncratic volatility is a proxy for MAX and once they control for it using value-weighted portfolios, the relation found in Ang et al. (2006, 2009) is reduced. When using equal-weighted portfolios, the relation is reversed.

Cao and Xu (2010) decompose volatility into a short- and long-run component. They find that stocks with high long-run volatility are positively related to expected returns, while those with high short-run volatility experience a negative relation. They propose a potential explanation for the conflicting results in previous studies, saying that different measures might capture different horizons of the volatility. This is also supported by the correlation found between Fu's (2009) measure and the measure for long-run volatility, and Ang et al.'s (2006) measure and the measure for short-run volatility, although moderately. The paper also concludes that the negative relation found in Ang et al. (2006) cannot fully be explained by return reversals, as suggested by Fu (2009) and Huang et al. (2010). Rachwalski and Wen (2013) also decompose idiosyncratic volatility in a similar way. They argue that recent information might not be entirely incorporated into prices, while historical information should be. They find a positive relation for distant idiosyncratic volatility and returns, and a negative relation for recent idiosyncratic volatility and returns. They do however argue that idiosyncratic risk innovations, rather than levels, are the cause of the negative relation. At the same time they can't rule out levels as a factor behind the anomaly found in Ang et al. (2006, 2009).

Boehme et al. (2009) consider visibility and short-sale interest instead and find a positive relationship between idiosyncratic risk and expected returns for firms with low visibility and limited short selling. The negative relation is apparent for firms with high visibility or high short selling, although not statistically significant.

Jiang, Xu, and Yao (2009) show that idiosyncratic volatility is inversely related to future earnings shocks, as well as future earnings. They confirm the results in Ang et al. (2006) but when controlling for earnings shocks, the significant and negative relation disappears. They argue that idiosyncratic volatility contains future earnings information.

Peterson and Smedema (2011) test the relationship between realized idiosyncratic volatility and returns as in Ang et al. (2006) and show that their results are robust in non-January months. Including all months, their results are similar to those of Bali and Cakici (2008). For January months, returns are increasing in idiosyncratic volatility and the results are significant for both value-weighted and equal-weighted portfolios. When excluding January in combination with equal-weighted portfolios, they do however find a negative relationship significant at the 5% level. They argue that the relation found in Ang et al. (2006) actually is robust for equal-weighted portfolios when excluding January. The negative relation is explained by mispricing, controlling for analyst coverage and forecasts dispersion. Following Fu (2009), they also confirm the positive relationship with expected returns, and show that it is strengthened when controlling for realized returns.

Guo, Kassa, and Ferguson (2014) question the use of EGARCH as seen in e.g. Fu (2009). They argue that the methodology introduces a look-ahead bias since estimation of EGARCH parameters includes the month t return, later used for constructing the expected month t idiosyncratic volatility. When the month t return is large, idiosyncratic volatility is biased upwards. The opposite is true for negative returns but the authors argue that this primarily yields a positive bias since there are more stocks with extreme positive returns as compared to negative. This results in a false positive relationship between EGARCH idiosyncratic volatility and stock returns, which is removed when correcting for the look-ahead bias. The paper does not confirm the findings of Ang et al. (2006, 2009), nor does it provide a clear view on the relationship. It does however rule out the positive relationship found for EGARCH idiosyncratic volatility.

2.4 Literature on the negative relationship between idiosyncratic volatility and returns

Since the findings of Ang et al. (2006), other authors have found support for the negative relation. Guo and Savickas (2010) extend the sample period to include pre-1962 U.S. data and find similar results to those of Ang et al. (2006), for all periods considered. Similar to Ang et al. (2009), they look at G7 countries for an extended period of time, also to confirm the negative relationship.

Chen et al. (2012) examine the robustness of the anomaly presented in Ang et al. (2006). They confirm the negative relationship when using value-weighted portfolios but only find insignificant results for raw returns once portfolios are equal-weighted, similar to Bali and Cakici (2008). Unlike Bali and Cakici (2008), Chen et al. (2012) find a significant negative relation between idiosyncratic volatility and risk-adjusted returns using both value- and equal-weighted portfolios. They also show that the results are driven by common stocks, as compared to non-common (certificates, ADRs), when using value-weighted portfolios. Further, they exclude microcaps (stocks below the 20th percentile of market capitalization on the NYSE) and penny stocks (stocks with prices below five dollars) to show that the results are rather robust when controlling for these. Also, when only looking at small and large cap stocks, i.e. excluding microcaps, that are also not penny stocks, the results are both significant and negative for value-weighted *and* equal-weighted portfolios. This suggests that microcaps and penny stocks are driving the insignificant results for equal-weighted portfolio returns. The authors are also able to dismiss the explanation of stock reversals as suggested by Fu (2009) and Huang et al. (2010), controlling for past returns in their regressions. They only present stock reversals as a concern for penny stocks, yielding less significant results and the opposite sign in one regression. Similar to Peterson and Smedema (2011) they find an even stronger relation when excluding January months.

A recent contribution on the subject is provided by Stambaugh, Yu, and Yuan (forthcoming). They present an explanation for the negative relation, arguing that investor reluctance or inability to sell underpriced stock short in combination with arbitrage risk[7] is the reason. Stocks with higher idiosyncratic volatility (higher arbitrage risk) are more likely to be mispriced. For overpriced stocks the effect of idiosyncratic volatility is negative while it is positive for underpriced stocks. Given that more arbitrage capital is allocated to long positions compared to short, more underpricing is eliminated and the negative effect of idiosyncratic risk outweighs the positive. The authors use averages of stock rankings with regard to eleven return anomalies to construct a proxy for mispricing, and then present evidence of the properties described above. The results are robust to excluding smaller firms and employing an equal weighting scheme.

[7] Risk that defers arbitrage, e.g. idiosyncratic risk.

Table 1

Summary of articles discussed in Literature review

Paper reports the author and year of publishing, Sample reports the sample studied in paper, Relation found reports the relation found between idiosyncratic volatility and returns, Weighting scheme reports the weighting scheme of portfolios used in portfolio approach, Idiosyncratic volatility estimation reports the method employed for the computation of idiosyncratic volatility, and Additional aspects reports findings in addition to the relation.

Paper	Sample	Relation found	Weighting scheme	Idiosyncratic volatility estimation	Additional aspects
Ang et al. (2006)	AMEX, NASDAQ, and NYSE July, 1963 - December, 2000	Negative	Value	1-month lagged idiosyncratic volatility, daily data	
Ang et al. (2009)	23 developed markets with focus on the U.S. (July, 1963 - December, 2003) and the G7 countries (January, 1980 - December, 2003)	Negative	Value	1-, 3-, 6-, and 12-month lagged idiosyncratic volatility, daily data	
Fu (2009)	AMEX, NASDAQ, and NYSE July, 1963 - December, 2006	Positive	Equal and value	EGARCH one-month-ahead expected idiosyncratic volatility	Return reversals are largely driving the results in Ang et al. (2006, 2009)
Huang et al. (2010)	AMEX, NASDAQ, and NYSE July, 1963 - December, 2004	Positive	N/A[1)]	EGARCH one-month-ahead expected idiosyncratic volatility	Return reversals are largely driving the results in Ang et al. (2006, 2009)
Eiling (2013)	AMEX, NASDAQ, and NYSE April, 1959 - December, 2009	Positive	Value	EGARCH one-month-ahead expected idiosyncratic volatility	Including industry-specific human capital explains the premium for idiosyncratic volatility to some extent
Spiegel and Wang (2005)	AMEX, NASDAQ, and NYSE January, 1962 - December, 2003	Positive	Value	EGARCH one-month-ahead expected idiosyncratic volatility	Liquidity is negatively correlated with IVOL and its impact on returns is small relative to idiosyncratic volatility
Brockman, Schutte, and Yu (2009)	44 developed and emerging markets July, 1980 - October, 2007	Positive[2)]	Equal and value	EGARCH one-month-ahead expected idiosyncratic volatility	Low investor wealth and high investor risk tolerance lead to larger idiosyncratic volatility premiums
Chua, Goh, and Zhang (2010)	AMEX, NASDAQ, and NYSE January, 1963 - December, 2003	Positive	Equal and value	Lagged idiosyncratic volatility (daily data) decomposed into expected/unexpected	
Bali and Cakici (2008)	AMEX, NASDAQ, and NYSE July, 1958 - December, 2004	Neg./Pos.	Equal and value	1-month (24 to 60-month) lagged idiosyncratic volatility, daily data (monthly data)	
Bali, Cakici, and Whitelaw (2011)	AMEX, NASDAQ, and NYSE July, 1962 - December, 2005	Neg./Pos.	Equal and value	1-month lagged idiosyncratic volatility[3)], daily data	Including "MAX" reverses the relationship found in Ang et al. (2006, 2009) under equal weighting
Cao and Xu (2010)	AMEX, NASDAQ, and NYSE January, 1963 - June, 2008	Neg./Pos.	N/A[4)]	Monthly rolling estimate of idiosyncratic volatility decomposed into short- and long-run components	
Rachwalski and Wen (2013)	CRSP and Compustat 1966 - 2011[5)]	Neg./Pos.	Equal and value	Lagged idiosyncratic volatility (daily data) decomposed into recent/distant	
Boehme et al. (2009)	NASDAQ and NYSE January, 1988 - June, 2002	Neg./Pos.	Equal and log-value	52-week lagged standard deviation of excess returns, weekly data	Investor recognition and short-selling activities affect the relationship between idiosyncratic volatility and returns
Jiang, Xu, and Yao (2009)	CRSP[6)] January, 1974 - December, 2002	Neg./Pos.	Equal	3-month lagged idiosyncratic volatility, daily data	Information about future earnings affects the relationship between idiosyncratic volatility and returns
Peterson and Smedema (2011)	AMEX, NASDAQ, and NYSE February, 1966 - December, 2008	Neg./Pos.	Equal and value	1-month lagged idiosyncratic volatility, daily data[7)]	For January months, returns are increasing in idiosyncratic volatility
Guo and Savickas (2010)	CRSP 1926 - 2005 for the U.S. and Datastream 1973 - 2003 for G7 countries	Negative	Value	1-month lagged idiosyncratic volatility, daily data[8)]	
Chen et al. (2012)	AMEX, NASDAQ, and NYSE 1963 - 2010	Negative	Equal and value	1-month lagged idiosyncratic volatility, daily data[9)]	Microcap and penny stocks reduce the negative relation between idiosyncratic volatility and returns
Stambaugh, Yu, and Yuan (forthcoming)	AMEX, NASDAQ, and NYSE August, 1965 - January, 2011	Negative	Equal and value	1-month lagged idiosyncratic volatility, daily data	Arbitrage risk and arbitrage asymmetry explain the negative relation

Lagged idiosyncratic volatility implies measuring idiosyncratic volatility relative to an asset pricing model, 1) Huang et al. (2010) do not sort stocks into portfolios under the EGARCH approach, 2) Brockman, Schutte, and Yu (2009) find a positive and significant relation in 36 out of 44 countries with the remaining eight also positive although insignificant, 3) Bali, Cakici, and Whitelaw (2011) measure idiosyncratic volatility relative to the market model (single-factor) but declare in a footnote that the three-factor model yields similar results, 4) Cao and Xu (2010) do not sort stocks into portfolios, 5) Rachwalski and Wen (2012) only report obtaining data from CRSP and Compustat. Their primary sample spans 1966 - 2011 to facilitate comparison with Ang et al. (2006). They consider the expanded sample 1929 - 2011, 6) Jiang, Xu and Yao (2009) only report obtaining data from CRSP, 7) Peterson and Smedema (2011) also use three measures of expected volatility, 8) Guo and Savickas (2008) estimate idiosyncratic volatility relative to the CAPM, and 9) Chen et al. (2012) estimate idiosyncratic volatility relative to a market model but find consistent results using the Fama-French three-factor model.

3 Methodology and data

In the following section we first explain the methods employed in our research, and then describe the data used. In the methodology subsection, we first explain our definitions and calculations of returns and the risk-free rate. Second, we define the measure of idiosyncratic volatility used in this study. After that, we present the portfolio approach employed to assess the relationship between idiosyncratic volatility and returns in the Swedish stock market. Finally, we explain and discuss the controls and alterations made to the portfolio approach and the data to test the robustness of our results.

In the data subsection, we first describe our sample and then move on to the sources of our proxies for the market portfolio and risk-free interest rate. We end with an explanation of our calculation and validation of factor returns in the Fama-French three-factor model.

3.1 Methodology

3.1.1 Return definition

To be consistent with Ang et al. (2006, 2009), we define returns as simple returns, meaning that the return on an asset from time $t-1$ to t is calculated as:

$$R_t = \frac{V_t}{V_{t-1}} - 1 \tag{1}$$

Where V_t is the asset value at time t and V_{t-1} is the asset value at time $t-1$.

3.1.2 Risk-free rate definition

In accordance with Fama and French (1993) and Ang et al. (2009), the proxy for the risk-free interest rate used in this study is the 1-month (the shortest available) Treasury bill rate for Sweden. When used to calculate daily and monthly excess returns, we deannualize it as follows:

$$r_{f,t} = (1 + \text{T-bill rate})^{1/n} - 1 \tag{2}$$

Where we assume 252 trading days and 12 months in a year.

3.1.3 Idiosyncratic volatility

Following the approach of Ang et al. (2006), we measure idiosyncratic volatility as lagged idiosyncratic volatility relative to the Fama-French three-factor model (henceforth FF-3F). Their preference for the FF-3F model over the CAPM is motivated by the relative failure of the CAPM to explain cross-sectional returns and the omnipresence of the FF-3F in empirical applications. The measurement of idiosyncratic volatility is conducted by running the following FF-3F regression:

$$R_{i,t} - r_{f,t} = \alpha_{i,t} + \beta_{i,t}(R_{m,t} - r_{f,t}) + s_{i,t}SMB_t + h_{i,t}HML_t + \varepsilon_{i,t} \tag{3}$$

Where $R_{i,t}$ is the return on portfolio i at time t, $r_{f,t}$ is the risk-free return, $(R_{m,t} - r_{f,t})$ is the excess return on the market portfolio, SMB_t is the difference between the average return on three small-size portfolios and the average return on three big-size portfolios, and HML_t is the difference between the average return on two high book-to-market portfolios and the average return on two low book-to-market portfolios.

In the base case approach, we run the regression using daily returns, and then obtain the residual standard deviation $\sigma_{\varepsilon_{i,t}}$ as the idiosyncratic volatility (henceforth IVOL) over the measured time-period.[8]

3.1.4 Portfolio approach

To investigate the relationship between IVOL and returns, we implement the $L/M/N$ portfolio formation strategy employed by Ang et al. (2006, 2009), consisting of an L-month estimation period, an M-month waiting period, and an N-month holding period. At the beginning of any month t, IVOLs are obtained by running the regression in equation (3) over an L-month period from month $t - L - M$ to month $t - M$, using daily returns. Then, at the beginning of month t, stocks are sorted

[8]The residual standard deviation is measured as the root mean squared error in the regression.

into quintile portfolios based on their IVOL, with quintile 1 (5) containing stocks with the lowest (highest) IVOL. After the formation, the portfolios are held over a period of N months, for which we then calculate value-weighted returns. Because of the value weighting of returns, we require the market value of shares outstanding at the end of month $t-1$ to be available for a stock from the full sample to be included in the IVOL sorting performed to form portfolios at the beginning of month t.

In line with Ang et al. (2006), our base case is the 1/0/1 portfolio formation strategy, where quintile portfolios are formed by sorting stocks based on their IVOL measured over the previous month using daily returns. Without any waiting period (i.e. M is equal to zero), these portfolios are held over a 1-month period, for which value-weighted raw and excess returns are calculated. The excess returns are then regressed on the factor returns in the FF-3F model to obtain risk-adjusted portfolio returns and assess whether or not the FF-3F model misprices the portfolios. This study includes raw returns mainly for illustrative purposes, while the main focus lies upon risk-adjusted returns, or alphas, measured relative to the FF-3F model. The reason for this is that differences in value-weighted raw returns between different IVOL quintiles could simply reflect different loadings on the FF-3F model factors. This means that any relation between IVOL and raw returns could simply reflect a relation between IVOL and systematic risk. This is further underlined by Guo and Savickas (2010), who point out that high IVOL stocks tend to have higher market betas than low IVOL stocks.

The return calculations and FF-3F regression are also performed for a zero-cost portfolio that is long (short) the quintile 5 (1) portfolio, containing stocks with the highest (lowest) IVOLs. We call this strategy the "5-1" and use it to further assess the relation between IVOL and returns in the Swedish stock market.

Ang et al. (2006) provide no explanation of how they treat delistings of stocks. Therefore, this study instead follows the approach of Piotroski (2000) and assumes a zero delisting return. If a stock is delisted during a month t, the return from the beginning of that month t through the delisting date is treated as the return on that stock for month t, meaning that delisted stocks are treated as cash until the next portfolio formation.

3.1.5 Controls and alterations to the portfolio approach

Ang et al. (2006) control for firm characteristics and market anomalies using a portfolio formation strategy where they first sort stocks into quintiles based on the firm characteristic or market anomaly and then, within each quintile, sort stocks based on IVOL. Having formed the 25 portfolios, they calculate average monthly returns as the average of the value-weighted returns on the five characteristic or anomaly portfolios in each IVOL quintile to control for the firm characteristic or anomaly. We employ this approach and, similar to Ang et al. (2006), control our findings for size, book-to-market, turnover, and momentum. The 25 portfolio approach can potentially provide a more detailed look on the relation between IVOL and returns in the Swedish stock market. It might also allow us to draw more detailed conclusions on whether or not two firm characteristics (size and book-to-market), extensively documented as influential for returns, and two market anomalies (turnover and momentum) affect the relationship between IVOL and returns in the Swedish stock market.

Turnover, found to be negatively related to expected returns by Datar, Naik, and Radcliffe (1998), is calculated at the beginning of any month t as the number of shares traded during month $t-1$ divided by the number of shares outstanding at the end of month $t-1$. Momentum, found to be positively related to expected returns by Jegadeesh and Titman (1993), is calculated at the beginning of any month t as the return on the stock over the previous six months.

In order to examine if the relation between IVOL and returns in the Swedish stock market depends on the horizon of the IVOL estimation period, we also use longer estimation windows (3-, 6-, 12-, and 24-month windows) to calculate IVOLs based on daily returns, similar to Ang et al. (2009). To further test the robustness of any potential relation, and to ensure that it is not driven by a specific time-period or event, we also use sub-sampling for the 1/0/1 portfolios. We examine the effect on the relationship between IVOL and returns of dividing the studied time period into two sub-samples (1994 to 2003 and 2004 to 2013) and excluding the crisis years of 2000 and 2008 from the base case 1/0/1 portfolio approach.

Given the findings of Bali and Cakici (2008), we also find it highly relevant to *separately* examine how an equal weighting scheme for the 1/0/1 portfolios and an estimation of IVOL using monthly returns over the past 24 to 60 months (as available) affects the relation between IVOL and returns in the Swedish stock market. With the findings of Peterson and Smedema (2011) and Chen et al. (2012) in mind, we then proceed to test how the results for the equal- and value-weighted 1/0/1 portfolios are affected by a separate exclusion of January months and microcap stocks.

Chen et al. (2012) follow the approach of Fama and French (2008) and define microcap stocks as stocks with a market capitalization below the 20th percentile of market capitalizations for NYSE stocks. This gives them an average microcap fraction of 47% of their entire stock sample (consisting of NYSE, AMEX, and NASDAQ stocks). In our sample, the stocks listed on the OMX lists[9] represent the best proxy for the NYSE reference group used by Fama and French (2008), in the sense that they in most cases are bigger and more well-known than stocks listed on the other Swedish lists. However, due to differences in the dispersion of market capitalizations between the U.S. and Swedish stock markets, following the approach of Fama and French (2008) and using the 20th percentile of market capitalizations for the OMX stocks in our sample as the microcap breakpoint gives us a much smaller average microcap fraction of about 19% of our entire stock sample.

In order to obtain a microcap fraction more equivalent to the microcap fraction in the U.S. market produced by the Fama and French (2008) approach, we instead opt for the microcap definition provided by the U.S. Securities and Exchange Commission, SEC (2013). The SEC defines microcap stocks as stocks with a market capitalization of less than $250 or $300 million. Using this definition, we set $275 million in relation to the maximum market capitalization of a U.S. company at the end of 2014 (Apple: $647,361 million) to obtain a breakpoint of about 0.04%.[10] In each month, before portfolios are formed, we then rid our sample of microcap stocks by excluding all stocks with a market capitalization of 0.04% or less of the maximum

[9] A-listan and O-listan prior to October 2, 2006, and OMX Small Cap, OMX Mid Cap, and OMX Large Cap from October 2, 2006, and onwards (see Table 3).

[10] The maximum U.S. market capitalization at the end of 2014 has been obtained from FT Global 500 Q4 2014.

market capitalization in that month. This produces a significantly larger average microcap fraction of about 30% of our entire stock sample.

3.2 Data

3.2.1 Sample construction

The full sample used in this study consists of all Swedish listed common stocks from July, 1994, through December, 2013 (see Table 3 for the lists included in the sample). For each stock, we obtain daily closing price, daily trading volume, monthly market capitalization, monthly number of shares, and year $t-1$ book value of equity. The data is collected from the Finbas database (which is free of survivorship bias) with the exception of complementary book values of equity from Bloomberg and company annual reports, which we obtain via Retriever. The daily closing prices are adjusted for dividends, splits, dilution and other corporate events, meaning that the raw returns calculated are gross returns. The full sample contains daily observations of closing prices and trading volume for a total of 1,099 unique stocks, stretching over a time period of 4,899 trading days, yielding a total of 2,114,462 observations. Table 2 shows summary statistics for the sample.

Table 2

Summary statistics for the daily number of stocks over time in the sample

	Full sample
Total*	1099
Min	276
Max	552
Mean	434
Median	432
Time period	July 1, 1994, to December 30, 2013

*The number of stocks varies over time

Table 3

Summary statistics for the lists included in the sample

The table reports the average number of stocks on the list for the time-period during which the list is included in the sample

List	Mean no. stock
Aktietorget	88
First North	69
Innovationsmarknaden	14
NGM Nordic MTF	20
Nordic Growth Market (NGM)	41
Nya Marknaden	18
OTC-listan	56
SBI-listan	50
A-listan*	117
O-listan*	190
OMX Small Cap*	100
OMX Mid Cap*	70
OMX Large Cap*	61

*Stocks listed on these lists are referred to as OMX stocks

3.2.2 Market return and risk-free interest rate

We use the Stockholm all-share index, OMXSPI, as a proxy for the market portfolio when calculating the market return. Data for the OMXSPI is obtained from NASDAQ OMX. As mentioned above, we use the Swedish 1-month Treasury bill rate, available from the Riksbank, as our risk-free interest rate.

3.2.3 Fama-French three-factor returns

We measure idiosyncratic volatility relative to the FF-3F model, but as no FF-3F returns for Sweden alone are available on Kenneth French's website, we construct them ourselves. We adopt the methodology of Fama and French (1993) to calculate the factor returns in the FF-3F model regression equation, specified in equation (3). The excess return on the OMXSPI over the Swedish 1-month Treasury bill rate is used as the excess market return and the stocks in our full sample are used to calculate the SMB and HML factor returns.

In accordance with Fama and French (1993), market value of shares outstanding for December of year $t-1$ and June of year t as well as book value of equity for year $t-1$ (reported at the end of December) must be available for a stock from the full sample to be included in the factor return calculation between July of year t and June of year $t+1$.

To calculate the SMB and HML factor returns, we use six portfolios formed by independently sorting stocks on size (market value of shares outstanding) and book-to-market (henceforth BtM) ratios. At the end of June each year t from 1994 to 2013, we sort all the stocks listed on the OMX lists on their size (market value of shares outstanding). We then calculate the median size of the OMX stocks and use it to divide all stocks used for the factor return calculation into two groups, small and big (S and B). Fama and French (1993) use NYSE breakpoints to assign NYSE, AMEX, and NASDAQ stocks to size and BtM groups. As mentioned above, the stocks in our sample that are listed on the OMX lists represent the best proxy for the NYSE reference group used by Fama and French (1993 and 2008), why we use those as our reference group for both size and BtM ratios.

At the end of June each year t from 1994 to 2013, we also sort all stocks listed on the OMX lists on their BtM ratios (book value of equity reported at the end of December of year $t-1$ divided by total market value of the company at the end of year $t-1$). We then calculate breakpoints for the bottom 30%, middle 40%, and top 30% of the sorted BtM ratios and divide all stocks used for the factor return calculation into three low, medium, and high groups (L, M, and H) using the breakpoints. Following Fama and French (1993), we do not include companies with negative BtM ratios in the portfolios.

After grouping the stocks into two size groups and three BtM groups, we form six portfolios from the group intersections (S/L, S/M, S/H, B/L, B/M, B/H). We then calculate daily and monthly value-weighted raw returns on the portfolios from July of year t through June of year $t+1$, at the end of which new portfolios are formed.[11]

Having formed the six portfolios and calculated their returns, we proceed to calculate the SMB and HML factor returns. The SMB factor return is the difference, at each time t, between the average return on the three small size portfolios (S/L,

[11] Both the daily and the monthly portfolio returns are value-weighted monthly, due to a lack of availability of daily market capitalization data (or the building blocks needed to calculate it) in the Finbas database.

S/M, S/H) and the average return on the three big size portfolios (B/L, B/M, B/H), calculated as:

$$SMB_t = \frac{R_{S/L,t} + R_{S/M,t} + R_{S/H,t}}{3} - \frac{R_{B/L,t} + R_{B/M,t} + R_{B/H,t}}{3} \tag{4}$$

The HML factor return is the difference, at each time t, between the average return on the two high BtM portfolios (S/H, B/H) and the average return on the two low BtM portfolios (S/L, B/L), calculated as:

$$HML_t = \frac{R_{S/H,t} + R_{B/H,t}}{2} - \frac{R_{S/L,t} + R_{B/L,t}}{2} \tag{5}$$

Table 4 presents summary statistics for the portfolios used to calculate the FF-3F model factor returns and Table 5 presents summary statistics for the factor returns.

Table 4

Summary statistics for the six portfolios used to calculate the factor returns in the Fama-French three-factor model

Mean reports the average monthly percentage return, Std. reports the standard deviation of monthly percentage returns, and No. of firms reports the monthly average number of firms.

	Book-to-market group		
Size group	Mean		
	Low	Middle	High
Small	0.74	1.16	0.97
Big	0.98	1.12	1.49
	Std.		
	Low	Middle	High
Small	8.03	6.46	5.29
Big	8.56	5.48	5.81
	No. of firms		
	Low	Middle	High
Small	77	83	75
Big	43	50	28

Table 5

Summary statistics for the monthly factor returns in the Fama-French three-factor model

Mean reports the average monthly percentage return and Std. reports the standard deviation of monthly percentage returns.

	$R_{m,t} - r_{f,t}$	SMB	HML
Mean	0.62	-0.24	0.37
Std.	5.72	3.93	5.34

Puzzlingly, we find the average monthly SMB factor return to be negative (see Table 5), which contradicts the findings of Fama and French (1993), and the theory that small stocks outperform big stocks. However, this is not unique, as Malin and Veeraraghavan (2004) and Eraslan (2013) find a negative average SMB factor return in the UK and the Turkish market, respectively. Actually, the averages of the monthly U.S. and European SMB factor returns provided on Kenneth French's website are also negative for the time-period examined in this study.[12] It seems the financial turmoil in the sample period is influential for the negative average SMB return, as an exclusion of the crisis years of 2000 (the tech bubble) and 2008 increases the average SMB return to approximately -0.1%.

To validate the factor returns, and test the explanatory power of our factor returns in the FF-3F model versus the CAPM, we form nine portfolios by performing two independent sortings on size and BtM and then use the value-weighted excess returns on these nine portfolios as the dependent variables in regressions on the three risk factors in the FF-3F model and the one risk factor in the CAPM. Fama and French (1993) use 25 portfolios, but because of the much smaller size of our sample, using 25 portfolios would lead to a high risk of obtaining portfolios with only one or even zero stocks. Therefore, we instead use nine portfolios, which are formed at the end of June of each year t. First, we sort the OMX stocks on size, calculate size breakpoints for the lower, middle, and upper third of stocks, and allocate all stocks to a lower, middle, or upper size group using these. Second, we sort the OMX stocks on BtM, and repeat the procedure of sorting and allocating all stocks to a lower,

[12]The average monthly SMB return between July, 1994, and December, 2013, is approximately -0.08% for the U.S. SMB factor and approximately -0.02% for the European SMB factor.

middle, and upper BtM group. As was the case in the calculation of the factor returns in the FF-3F model, market capitalization for December of year $t-1$ and June of year t as well as book value of equity for year $t-1$ (reported at the end of December) must be available for a stock from the full sample to be included in the formation of the nine portfolios.

Having formed the portfolios, we calculate value-weighted excess returns on them from July of year t through June of year $t+1$, which we then use as the dependent variables in regressions on the FF-3F returns and the excess market return (the one risk factor in the CAPM). Table 6 shows the results of the FF-3F model and CAPM regressions for the nine portfolios sorted on size and BtM. As can be seen from the R-squared values, the FF-3F model does a much better job than the CAPM in explaining the returns on the nine portfolios. Additionally, the FF-3F model produces only one regression alpha that is significant at the 5% level or lower while the CAPM produces three. This indicates that the FF-3F model using our calculated factor returns is superior to the CAPM in explaining returns in the Swedish stock market.

Table 6

Summary statistics: Regressions of monthly excess portfolio returns on the three Fama-French factor returns and the one CAPM factor return

The time-period studied is July, 1994, through December, 2013. At the end of June of each year t, we form nine portfolios by independently sorting the sampled OMX stocks on size and BtM, calculating independent size and BtM breakpoints for the lower, middle, and upper third of the OMX stocks, and then using those breakpoints to assign all stocks to size and BtM groups. We then calculate monthly value-weighted excess returns for the nine portfolios from July of year t through June of year $t+1$ and use these as the dependent variable in regressions on the monthly returns on three Fama-French factors and the one CAPM factor. Robust Huber-White t-statistics are reported in brackets.

	Fama-French three-factor reg: $R_{i,t} - r_{f,t} = \alpha_{i,t} + \beta_{i,t}(R_{m,t} - r_{f,t}) + s_{i,t}SMB_t + h_{i,t}HML_t + \varepsilon_{i,t}$		
	Book-to-Market group		
Size group	1	2	3
		α	
1	0.0025	0.0015	0.0010
	[1.05]	[0.60]	[0.53]
2	0.0019	0.0020	0.0047
	[0.93]	[1.10]	[2.75]
3	0.0016	0.0014	0.0030
	[1.39]	[0.95]	[1.87]
		β	
1	1.0526	1.1563	1.0117
	[22.86]	[15.23]	[20.34]
2	1.1492	1.1062	0.9865
	[18.71]	[23.16]	[20.69]
3	1.0586	0.9681	1.1102
	[41.26]	[29.18]	[33.77]
		s	
1	1.1876	1.0857	0.9573
	[16.21]	[8.79]	[12.05]
2	0.7528	0.4884	0.4959
	[10.90]	[8.37]	[8.22]
3	-0.2143	-0.0606	0.0117
	[-6.56]	[-1.34]	[0.25]
		h	
1	-0.2863	0.0779	0.3730
	[-3.79]	[0.75]	[6.60]
2	-0.1886	0.2632	0.4231
	[-2.83]	[5.15]	[8.24]
3	-0.5100	0.2903	0.6118
	[-15.57]	[7.18]	[14.12]
		R^2	
1	0.8393	0.7498	0.7990
2	0.8499	0.7997	0.7791
3	0.9525	0.8407	0.8396

	CAPM one-factor reg: $R_{i,t} - r_{f,t} = \alpha_{i,t} + \beta_{i,t}(R_{m,t} - r_{f,t}) + \varepsilon_{i,t}$		
	Book-to-Market group		
Size group	1	2	3
		α	
1	-0.0013	0.0004	0.0021
	[-0.31]	[0.11]	[0.70]
2	-0.0005	0.0031	0.0068
	[-0.18]	[1.39]	[3.11]
3	-0.0015	0.0034	0.0071
	[-0.77]	[2.04]	[3.06]
		β	
1	1.0228	0.9646	0.6953
	[13.77]	[10.44]	[13.15]
2	1.1337	0.9095	0.7113
	[15.59]	[18.78]	[15.53]
3	1.3359	0.8361	0.8123
	[27.01]	[19.11]	[13.38]
		R^2	
1	0.4745	0.4843	0.4445
2	0.6777	0.7061	0.5954
3	0.8784	0.7730	0.6179

4 Empirical findings and analysis

In this section, we present and analyze our findings. First, the results of the base case portfolio approach are presented and analyzed. After that, the results from controlling for firm characteristics and market anomalies are presented and analyzed. Next, we present and analyze the results of altering the IVOL estimation periods, employing an equal weighting scheme, separately excluding January months and microcaps, and using sub-periods. The controls and alterations to our portfolio approach are then summarized and the robustness of the findings is discussed. Finally, we elaborate on some of the limitations of the methodology giving rise to our results.

4.1 The relation between IVOL and returns – base case

Table 7 shows the results of our base case 1/0/1 portfolio approach with value-weighted returns. In line with the findings of Ang et al. (2006), the highest IVOL portfolio (quintile 5) contains a very small part (1.23%) of the entire market, and stocks with high IVOL are characterized as being smaller and having a higher BtM ratio. As mentioned by Ang et al. (2006), the FF-3F model predicts that because of the size and BtM characteristics, the portfolio with high IVOL stocks should have high, not low, average returns.

Moving from IVOL quintile 1 to IVOL quintile 5, we see decreasing average returns and alphas, although portfolio 1 has a lower alpha than portfolio 2 and 3, similar to the results of Ang et al. (2006). The strategy of going long (short) high (low) IVOL stocks (the "5-1") yields a negative average return of -1.81% and an FF-3F alpha of -1.60% per month significant at the 1% level. This alpha is the difference between the portfolio 5 and portfolio 1 alphas, and since it is negative and statistically significant, the FF-3F model is unable to price the quintile 1 and quintile 5 portfolios, as is the case in Ang et al. (2006). The negative return of the 5-1 strategy also contradicts the FF-3F prediction that small stocks with high BtM ratios should have relatively high average returns. These findings suggest a statistically significant *negative* relation between IVOL and risk-adjusted returns in the Swedish stock market.

Table 7

Summary statistics for the base case portfolio approach

The time-period studied is July, 1994, through December, 2013. At the beginning of each month t, we form five portfolios by sorting the sampled stocks on realized idiosyncratic volatility relative to the Fama-French three-factor model over the previous month. We then calculate monthly value-weighted raw and excess returns for the five portfolios, and the difference in the aforementioned returns between quintile 5 and quintile 1. Mean reports the average monthly raw percentage return. The difference in raw returns between quintile 5 and quintile 1 is then t-tested, and the resulting t-statistic is reported in brackets below the mean 5-1 raw return difference. Finally, the excess returns are regressed on the factor returns in the Fama-French three-factor model. Alpha reports the alpha in the Fama-French three-factor regression, and robust Huber-White t-statistics are reported in brackets below the alphas. % Market share reports the portfolio's share of total market capitalization of all sampled stocks, Size reports the average log market value of shares outstanding, and BtM reports the average book-to-market ratio.

	IVOL quintile					
	1	2	3	4	5	5-1
Mean	1.00	1.20	1.14	0.86	-0.80	-1.81
						[-3.12]
Alpha	0.19	0.26	0.23	-0.03	-1.40	-1.60
	[1.54]	[1.52]	[0.82]	[-0.10]	[-3.14]	[-3.31]
% Market share	60.72	23.63	10.57	3.85	1.23	
Size	21.64	21.06	20.15	19.05	17.77	
BtM	0.67	0.63	0.67	0.72	0.89	

4.2 Controlling for firm characteristics and market anomalies

4.2.1 Controlling for size

Panel A of Table 8 reports our findings when 25 portfolios are formed by sorting stocks first on size and then on IVOL within each size quintile. The findings are very similar to those of Ang et al. (2006), with quintiles 2 to 4 having highly significant 5-1 alphas while the smallest and largest quintiles are insignificant. The 5-1 alphas of quintiles 2 to 4 are also of greater magnitude.

From Table 7 we see that size is decreasing in IVOL. The quintile portfolio with highest IVOL has the lowest average size. This raises the question of whether or not small stocks are driving the results. Judging by Panel A of Table 8, that does not seem to be the case, since the 5-1 strategy yields a much less negative alpha for size quintile 1 than for size quintiles 2 to 4, and the alpha for size quintile 1 is insignificant.

Looking at the overall patterns in each of the size quintiles, both the average returns and the alphas are lowest for the portfolio with the highest IVOL for all size quintiles except one. This indicates that size overall is not driving the effect, and that is further underlined by the results of controlling for size by averaging over all five size quintiles in each IVOL quintile. This yields a negative average return and a highly significant alpha of -1.25% per month (see Panel A of Table 8).

4.2.2 Controlling for book-to-market

Panel B of Table 8 reports our findings when 25 portfolios are formed by sorting stocks first on BtM ratios and then on IVOL within each BtM quintile. Overall we still see the negative relation moving from low IVOL stocks to high IVOL stocks. Stocks with the lowest and highest BtM ratios (quintiles 1 and 5) have negative alphas of -1.58% and -1.77% per month, respectively, for the 5-1 strategy. Both alphas are significant at the 5% level. For quintiles 2 to 4, the alphas for the 5-1 strategy are insignificant but the signs are coherently negative.

Table 7 shows that BtM is increasing in IVOL. The stocks with highest IVOL have highest average BtM ratios. Similarly to the case of size, this raises the question of whether or not stocks with high BtM ratios are driving the results. From the results in Table 8 that does not seem to be the case, since the 5-1 strategy produces negative and significant alphas for both BtM quintiles 1 and 5. In four out of five BtM quintiles, the average return is lowest in IVOL quintile 5, further indicating that BtM overall is not driving the results. As was the case when controlling for size, the indication is further underlined when controlling for BtM by averaging over the five BtM portfolios in each IVOL quintile, which yields a highly significant alpha of -1.18% per month for the 5-1 strategy (see Panel B of Table 8).

Table 8

Summary statistics for firm characteristic and market anomaly controls

The time-period studied is July, 1994, through December, 2013. At the beginning of each month t, 25 portfolios are formed by first sorting the stocks on the characteristic or anomaly, and then sorting the stocks within each characteristic or anomaly quintile on realized idiosyncratic volatility over the previous month. We then calculate monthly value-weighted raw and excess returns for the 25 portfolios, the difference in the aforementioned returns between IVOL quintile 5 and IVOL quintile 1 within each characteristic or anomaly quintile, and the average raw and excess return across all firm characteristic or market anomaly quintiles within each IVOL quintile. Finally, the excess returns are regressed on the factor returns in the Fama-French three-factor regression. The Control row reports results for averaging across all characteristic or anomaly quintiles. Mean reports the average monthly raw percentage return and Alpha reports the alpha in the Fama-French three-factor regression. Robust Huber-White t-statistics are reported in brackets.

Panel A: Portfolios sorted first on size and then on IVOL within each size quintile

	IVOL quintile							IVOL quintile					
Size quintile	1	2	3	4	5	5-1	Size quintile	1	2	3	4	5	5-1
	Mean							Alpha					
1	1.05	1.66	1.17	1.65	0.61	-0.44	1	0.55	1.15	0.61	1.06	-0.04	-0.59
								[1.17]	[2.44]	[1.10]	[1.67]	[-0.05]	[-0.65]
2	1.38	1.22	1.39	1.92	-0.77	-2.15	2	0.68	0.54	0.84	1.07	-1.25	-1.94
								[2.81]	[1.92]	[2.29]	[0.90]	[-2.71]	[-3.75]
3	1.59	1.39	1.08	0.16	-0.69	-2.28	3	0.88	0.65	0.38	-0.53	-1.31	-2.19
								[4.29]	[2.99]	[1.53]	[-2.00]	[-3.50]	[-5.10]
4	1.56	1.47	1.23	0.91	0.28	-1.28	4	0.72	0.61	0.37	0.09	-0.48	-1.20
								[3.63]	[3.03]	[1.66]	[0.37]	[-1.62]	[-3.43]
5	1.08	0.98	0.89	1.70	0.94	-0.14	5	0.31	0.02	-0.05	0.78	-0.01	-0.32
								[1.47]	[0.10]	[-0.26]	[3.27]	[-0.03]	[-0.68]
Control	1.33	1.34	1.15	1.27	0.07	-1.26	Control	0.63	0.59	0.43	0.49	-0.62	-1.25
								[4.26]	[4.09]	[2.56]	[1.55]	[-2.13]	[-3.74]

Panel B: Portfolios sorted first on BtM and then on IVOL within each BtM quintile

	IVOL quintile							IVOL quintile					
BtM quintile	1	2	3	4	5	5-1	BtM quintile	1	2	3	4	5	5-1
	Mean							Alpha					
1	1.03	1.44	0.88	0.57	-0.83	-1.86	1	0.35	0.73	0.07	0.06	-1.24	-1.58
								[1.30]	[2.23]	[0.15]	[0.11]	[-1.62]	[-1.97]
2	0.96	1.16	0.60	0.36	-0.45	-1.41	2	-0.02	0.23	-0.35	-0.46	-0.99	-0.97
								[-0.09]	[0.82]	[-0.99]	[-1.07]	[-1.69]	[-1.51]
3	1.36	1.12	1.19	-0.01	0.25	-1.11	3	0.42	0.14	0.26	-0.99	-0.42	-0.84
								[1.93]	[0.50]	[0.81]	[-2.44]	[-0.76]	[-1.41]
4	1.41	1.43	1.16	1.01	0.59	-0.83	4	0.32	0.30	0.10	0.04	-0.41	-0.73
								[1.54]	[1.02]	[0.20]	[0.08]	[-0.38]	[-0.67]
5	1.82	1.66	1.42	0.71	0.06	-1.76	5	0.87	0.60	0.34	-0.51	-0.90	-1.77
								[2.98]	[1.60]	[0.77]	[-0.81]	[-1.22]	[-2.44]
Control	1.32	1.36	1.05	0.53	-0.07	-1.39	Control	0.38	0.40	0.08	-0.37	-0.79	-1.18
								[3.80]	[2.47]	[0.44]	[-1.54]	[-2.09]	[-3.06]

Panel C: Portfolios sorted first on turnover and then on IVOL within each turnover quintile

Turnover quintile	IVOL quintile 1	2	3	4	5	5-1
	Mean					
1	0.64	1.09	-0.46	-1.15	-1.41	-2.05
2	0.89	0.82	0.52	-0.19	-1.64	-2.53
3	1.17	1.20	0.66	0.56	0.16	-1.01
4	1.01	1.00	1.42	1.49	1.09	0.08
5	1.41	1.34	1.55	2.16	0.60	-0.81
Control	1.02	1.09	0.74	0.57	-0.24	-1.26

Turnover quintile	IVOL quintile 1	2	3	4	5	5-1
	Alpha					
1	-0.07	0.27	-1.28	-1.67	-1.98	-1.91
	[-0.21]	[1.03]	[-2.89]	[-2.71]	[-2.30]	[-2.07]
2	-0.03	-0.03	-0.27	-0.76	-2.13	-2.11
	[-0.11]	[-0.10]	[-0.86]	[-1.68]	[-3.65]	[-3.31]
3	0.33	0.22	-0.35	-0.23	-0.18	-0.52
	[1.22]	[0.69]	[-0.91]	[-0.58]	[-0.30]	[-0.73]
4	0.17	0.12	0.50	0.74	0.10	-0.08
	[0.71]	[0.41]	[1.20]	[1.49]	[0.18]	[-0.13]
5	0.44	0.40	0.63	1.17	-0.25	-0.69
	[2.21]	[1.63]	[2.03]	[2.24]	[-0.37]	[-0.97]
Control	0.17	0.20	-0.15	-0.15	-0.89	-1.06
	[1.48]	[1.42]	[-0.85]	[-0.59]	[-2.53]	[-2.79]

Panel D: Portfolios sorted first on momentum and then on IVOL within each momentum quintile

Momentum quintile	IVOL quintile 1	2	3	4	5	5-1
	Mean					
1	0.76	0.48	-0.71	-0.68	-0.42	-1.18
2	1.60	0.42	0.57	0.79	-0.68	-2.28
3	0.94	1.65	1.01	0.63	0.13	-0.81
4	1.54	1.43	1.12	1.02	-0.65	-2.19
5	1.14	1.60	1.46	1.15	-0.28	-1.42
Control	1.20	1.12	0.69	0.58	-0.38	-1.58

Momentum quintile	IVOL quintile 1	2	3	4	5	5-1
	Alpha					
1	-0.26	-0.46	-1.56	-1.31	-1.03	-0.78
	[-0.38]	[-0.85]	[-2.15]	[-1.86]	[-1.03]	[-0.70]
2	0.62	-0.61	-0.32	-0.23	-1.34	-1.96
	[1.75]	[-1.69]	[-0.72]	[-0.31]	[-2.53]	[-3.15]
3	-0.06	0.75	-0.03	-0.35	-0.59	-0.54
	[-0.21]	[2.38]	[-0.07]	[-1.08]	[-1.24]	[-1.00]
4	0.62	0.53	0.23	0.08	-1.34	-1.96
	[2.28]	[1.96]	[0.85]	[0.25]	[-3.18]	[-3.84]
5	0.34	0.70	0.75	0.42	-0.97	-1.32
	[1.11]	[1.92]	[1.79]	[0.73]	[-1.40]	[-1.83]
Control	0.25	0.18	-0.19	-0.28	-1.06	-1.31
	[1.57]	[1.09]	[-0.85]	[-1.15]	[-3.15]	[-3.65]

4.2.3 Controlling for turnover

After forming 25 portfolios by sorting stocks first on turnover and then on IVOL within each turnover quintile, our results show that turnover quintiles 1 and 2 have larger differences in alphas (-1.91% and -2.11% per month) for the 5-1 strategy compared to quintiles 3 to 5, and the alphas of quintiles 1 and 2 are significant while those of quintiles 3 to 5 are not (see Panel C of Table 8). Ang et al. (2006) do not tabulate a similar 5x5 matrix for turnover but report that alphas for the 5-1 strategy are more pronounced in the highest turnover quintile. Thus, our findings contrast theirs since we find the largest difference in the second lowest turnover quintile.

The fact that only turnover quintiles 1 and 2 yield significant negative alphas for the 5-1 strategy could be seen as an indication that stocks with low turnover may be driving our results. However, in four out of the five turnover quintiles, the portfolio with highest IVOL has the lowest average return, and the negative relation between IVOL and risk-adjusted returns remains significant after our control for turnover (see Panel C of Table 8). This means that the case for turnover being the explanation for the negative relation between IVOL and risk-adjusted returns is weak, and that turnover at most can be seen as a partial explanation.

4.2.4 Controlling for momentum

Ang et al. (2006) motivate controlling for momentum by stating that an overrepresentation of past losers in the high IVOL quintile could cause a negative relation between IVOL and returns. To assess if this is the case in the Swedish stock market, we form 25 portfolios by first sorting stocks on momentum, i.e. return over the past six months, and then on IVOL within each momentum quintile.

The momentum effect is apparent when we compare average monthly returns for momentum quintiles 1 and 5. For all IVOL quintiles, the average monthly return is higher for past winners (momentum quintile 5) than past losers (momentum quintile 1). The 5-1 strategy yields negative FF-3F alphas across all momentum quintiles, and the alphas are significant for quintiles 2, 4 and 5 (alphas of -1.96%, -1.96%, and -1.32%, respectively). This indicates that momentum is not driving the results. Within each momentum quintile, high IVOL stocks on average do worse than low

IVOL stocks, further indicating that what is driving the results in the base case is not an overrepresentation of past losers within the high IVOL quintiles. Finally, the negative relationship between IVOL and risk-adjusted returns survives our control for momentum, which produces a highly significant alpha of -1.31% for the 5-1 strategy (see Panel D of Table 8 for results). This means that we have a strong case for disregarding momentum as an explanation of the negative relation between IVOL and risk-adjusted returns in the Swedish stock market.

4.3 Portfolio approach alterations

4.3.1 Different estimation periods

In Panels A, B, C, and D of Table 9 we report average returns, alphas, and their corresponding t-statistics when IVOL is estimated over 3, 6, 12, and 24 months, rather than over one month (still using daily returns). For the 3-, 6-, 12-, and 24-month estimation periods, the stocks with the highest IVOL as well as the 5-1 strategy yield negative and highly significant alphas. The alphas of the 5-1 strategy in the 3-, 6-, 12-, and 24-month estimations are even greater in magnitude compared to our base case 1/0/1 portfolio approach. This supports the notion that volatility is persistent over time (e.g. Engle, 1982), mentioned by Ang et al. (2009).

Ang et al. (2009) use 3-, 6-, and 12-month estimation periods and find the strongest IVOL effect using 3- and 6-month estimation periods as compared to 1-month. They also report decreasing coefficients moving from 3-month to 12-month estimation periods, which is somewhat different to our results as we obtain the most negative alpha for the 5-1 strategy (-1.80%) under the 6-month approach.[13] However, our results exhibit a similar trend when we move from 6-month to 24-month estimation periods, which causes the alphas of the 5-1 strategy to decrease in magnitude.

In Panel E of Table 9, we report average returns, alphas, and their corresponding t-statistics when IVOL is estimated over 24 to 60 months using monthly returns. When Bali and Cakici (2008) compute IVOL over the previous 24 to 60 months using

[13] The results of Ang et al. (2009) are achieved using Fama-MacBeth regressions.

monthly returns, they find that the 5-1 strategy produces negative and significant alphas for their full sample and negative and insignificant alphas for NYSE stocks. Our use of a 24 to 60 month estimation period yields a negative and significant alpha for the stocks with the highest IVOL as well as the 5-1 strategy. The pattern of average returns is increasing in IVOL for quintiles 2 to 3 and then decreasing, with the 5th quintile still yielding the lowest average return.

The relationship between IVOL and risk-adjusted returns remains negative and significant when altering the estimation periods and return frequencies, indicating that the negative relation is independent of these alterations.

Table 9

Summary statistics for different IVOL estimation periods and return frequencies

The time-period studied is July, 1994, through December, 2013. At the beginning of each month t, we form five portfolios by sorting the sampled stocks on realized idiosyncratic volatility relative to the Fama-French three-factor model over the specified period using the specified return frequency. We then calculate monthly value-weighted raw and excess returns for the five portfolios, and the difference in the aforementioned returns between quintile 5 and quintile 1. The excess returns are then regressed on the factor returns in the Fama-French three-factor model. Mean reports the average monthly raw percentage return and Alpha reports the alpha in the Fama-French three-factor regression. Robust Huber-White t-statistics are reported in brackets.

Panel A: 3-month estimation period using daily returns						
	IVOL quintile					
	1	2	3	4	5	5-1
Mean	1.14	1.07	1.00	1.04	-0.91	-2.05
Alpha	0.31	0.11	-0.06	0.31	-1.45	-1.75
	[2.78]	[0.59]	[-0.23]	[0.61]	[-2.84]	[-3.32]

Panel B: 6-month estimation period using daily returns						
	IVOL quintile					
	1	2	3	4	5	5-1
Mean	1.11	1.36	1.07	0.38	-1.00	-2.11
Alpha	0.27	0.41	0.07	-0.28	-1.53	-1.80
	[2.46]	[2.33]	[0.16]	[-0.79]	[-3.29]	[-3.69]

Panel C: 12-month estimation period using daily returns						
	IVOL quintile					
	1	2	3	4	5	5-1
Mean	1.07	1.10	1.28	0.24	-0.93	-2.00
Alpha	0.25	0.17	0.34	-0.39	-1.48	-1.74
	[2.29]	[0.92]	[0.75]	[-1.12]	[-3.19]	[-3.65]

Panel D: 24-month estimation period using daily returns						
	IVOL quintile					
	1	2	3	4	5	5-1
Mean	0.96	1.36	1.44	0.14	-0.97	-1.93
Alpha	0.17	0.54	0.48	-0.46	-1.48	-1.65
	[1.45]	[2.43]	[1.63]	[-1.36]	[-3.12]	[-3.31]

Panel E: 24- to 60-month estimation period using monthly returns						
	IVOL quintile					
	1	2	3	4	5	5-1
Mean	1.02	1.02	1.21	1.16	-0.26	-1.28
Alpha	0.23	0.18	0.31	0.35	-0.81	-1.04
	[1.59]	[0.88]	[1.09]	[1.14]	[-1.93]	[-2.21]

4.3.2 Equal weighting scheme

When Bali and Cakici (2008) employ an equal weighting scheme, they find insignificant and in many cases positive alphas for the 5-1 strategy under all specifications except when they consider only NYSE stocks, which yields a negative and significant alpha. When we employ an equal weighting scheme, the negative relationship between IVOL and risk-adjusted returns is non-existent, as can be seen in Panel A of Table 11. Our equal-weighted portfolios yield positive alphas across all quintiles, with four of them being significant; quintiles 1 and 2 at the 1% level, quintile 3 at the 5% level, and quintile 4 at the 10% level. The 5-1 strategy yields a positive alpha of 0.16%, although not significant. This indicates that the weighting scheme might actually be driving our base case findings, as well as the findings of Ang et al. (2006).

The average returns on four out of five IVOL quintile portfolios are higher when portfolios are equal-weighted than when they are value-weighted, indicating that stocks with higher average returns are now assigned larger weights and/or that stocks with lower average returns are now assigned lower weights compared to the value weighting scheme.

Table 10

Summary statistics for size and return differences in each IVOL quintile under the base case portfolio approach

Microcap share reports the average percentage share of stocks in the portfolio that are microcap stocks, Non-micro size reports the average log market value of shares outstanding of non-microcap stocks, Micro size reports the average log market value of shares outstanding of microcap stocks, Non-micro return reports the average monthly percentage return for non-microcap stocks in the quintile portfolio, and Micro return reports the average monthly percentage return for microcap stocks in the quintile portfolio.

IVOL quintile	1	2	3	4	5
Microcap share	11.73	10.52	20.58	41.66	68.06
Non-micro size	22.29	21.43	20.76	20.18	19.77
Micro size	17.02	17.91	17.84	17.62	17.04
Non-micro return	1.50	1.40	1.00	0.50	-0.94
Micro return	0.12	1.55	1.51	2.26	2.04

As can be seen from Table 10, microcaps on average outperform non-microcaps in IVOL quintiles 2 to 5, and the relation between IVOL and returns actually looks positive for the smallest stocks in the sample and negative for the rest. This indicates that the smallest stocks, which are assigned larger weights in the equal weighting scheme (especially in IVOL quintile 5 since that contains the largest fraction of microcap stocks), could be reducing the negativity of the relation found in the base case and causing the insignificant results for the equal-weighted portfolio approach.

Table 11

Summary statistics for alteration of weighting scheme and exclusion of January months and microcap stocks

The time-period studied is July, 1994, through December, 2013. At the beginning of each month t, we form five portfolios by sorting the sampled stocks on realized idiosyncratic volatility relative to the Fama-French three-factor model over the previous month. We then calculate monthly equal- and value-weighted raw and excess returns for the five portfolios, and the difference in the aforementioned returns between quintile 5 and quintile 1. The excess returns are then regressed on the factor returns in the Fama-French three-factor model. Mean reports the average monthly raw percentage return and Alpha reports the alpha in the Fama-French three-factor regression. Robust Huber-White t-statistics are reported in brackets.

	Equal-weighted portfolios							**Value-weighted portfolios**					
Panel A: Base case portfolio results*													
	IVOL quintile							IVOL quintile					
	1	2	3	4	5	5-1		1	2	3	4	5	5-1
Mean	1.39	1.39	1.08	1.54	1.28	-0.10	Mean	1.00	1.20	1.14	0.86	-0.80	-1.81
Alpha	0.58	0.56	0.34	0.79	0.74	0.16	Alpha	0.19	0.26	0.23	-0.03	-1.40	-1.60
	[3.44]	[4.71]	[2.44]	[1.76]	[1.55]	[0.30]		[1.54]	[1.52]	[0.82]	[-0.10]	[-3.14]	[-3.31]
Panel B: Excluding January months													
	IVOL quintile							IVOL quintile					
	1	2	3	4	5	5-1		1	2	3	4	5	5-1
Mean	1.33	1.22	0.76	0.24	-0.24	-1.57	Mean	1.00	1.14	1.15	0.47	-1.41	-2.41
Alpha	0.60	0.54	0.28	-0.04	-0.33	-0.93	Alpha	0.22	0.18	0.27	-0.11	-1.50	-1.71
	[3.24]	[4.93]	[1.97]	[-0.19]	[-0.94]	[-2.25]		[1.62]	[1.07]	[0.97]	[-0.32]	[-3.10]	[-3.32]
Panel C: Excluding microcap stocks													
	IVOL quintile							IVOL quintile					
	1	2	3	4	5	5-1		1	2	3	4	5	5-1
Mean	1.56	1.39	1.37	0.88	0.09	-1.47	Mean	1.02	1.09	1.36	1.30	0.36	-0.66
Alpha	0.72	0.52	0.52	0.08	-0.56	-1.28	Alpha	0.24	0.13	0.43	0.32	-0.44	-0.68
	[4.33]	[4.01]	[3.81]	[0.53]	[-2.46]	[-4.33]		[1.77]	[0.82]	[1.69]	[1.19]	[-1.27]	[-1.73]

*The results for the base case value-weighted portfolios are the same as presented in Table 7

4.3.3 The January effect – exclusion of January months

Keim (1983) documents that small stocks have far outperformed larger stocks in January months, but not in other months. When we exclude January months under the value weighting scheme, the 5-1 strategy produces a more negative average return

(-2.41%) as well as a more negative alpha (-1.71%) compared to the base case (see Panel B of Table 11). The alpha is significant at the 1% level. This lends credibility to the indication that the smallest stocks are reducing the negativity of the relation found between IVOL and risk-adjusted returns in the base case. This is further underlined when we exclude January months under the equal weighting scheme. As can be seen in Panel B of Table 11, the alpha produced by the 5-1 strategy changes sign when January months are excluded, and the average return of the 5-1 strategy is reduced by more than 1 percentage point. The alpha of -0.93% per month is significant at the 5% level. Now, alphas and average returns decrease when moving from low IVOL stocks to high IVOL stocks also under the equal weighting scheme.

4.3.4 Exclusion of microcaps

As can be seen in Panel C of Table 11, excluding microcaps under the value weighting scheme causes the alpha of the 5-1 strategy to decrease in absolute terms (from -1.60% to -0.68%), and simultaneously in significance. The alpha is now significant at the 10% level. The pattern of decreasing average returns and alphas is apparent moving from quintile 3 to 5.

At first glance, this result is quite puzzling. Since the smallest stocks in IVOL quintile 5 seem to have reduced the negativity of the relation between IVOL and risk-adjusted returns, one would expect the relation to become *more* negative when they are excluded. However, because of the value weighting scheme, the negativity of the relation between IVOL and returns is *reduced*. When microcaps are excluded, the new post-exclusion IVOL quintile 5 portfolio will consist to about 46% of stocks from the pre-exclusion IVOL quintile 5 portfolio and to about 54% of stocks from the pre-exclusion IVOL quintile 4 portfolio. As can be seen in Table 10, the average return of the non-microcap stocks in the pre-exclusion IVOL quintile 4 portfolio is much higher than the average return of the non-micro stocks in the pre-exclusion IVOL quintile 5 portfolio. Since the post-exclusion IVOL quintile 5 portfolio will consist of more stocks from the pre-exclusion IVOL quintile 4 portfolio, those will dominate. Furthermore, Table 10 shows that the non-microcap stocks in the pre-exclusion IVOL quintile 4 portfolio on average are larger in size than those in the pre-exclusion IVOL quintile 5 portfolio. This means that the dominance of the stocks from the pre-exclusion IVOL quintile 4 portfolio in the post-exclusion IVOL quintile 5 portfolio will be amplified by the value weighting scheme. Because of this, the average return on the post-exclusion IVOL quintile 5 portfolio is more than 1 percentage point higher than that on the pre-exclusion IVOL quintile 5 portfolio. Therefore, excluding microcaps reduces the negative relation between IVOL and returns in terms of average return, alpha, and significance. Had we employed the approach of Chen et al. (2012), and used IVOL decile portfolios rather than quintile portfolios, it is likely that the high IVOL minus low IVOL strategy (the "10-1" in that case) would have yielded a more negative average return and alpha than the quintile portfolio approach when excluding microcaps.

When microcaps are excluded under the equal weighting scheme, the negative relation between IVOL and risk-adjusted returns reemerges. As can be seen in Panel C of Table 11, the 5-1 strategy now yields a highly significant alpha of -1.28% for the equal weighting scheme. Once again, we see a decreasing pattern in average returns and alphas, with only one of them being insignificant. These findings further verify the indication that the smallest stocks are causing the insignificant results for the equal-weighted portfolio approach.

4.3.5 Using sub-samples

As can be seen in Table 12, the negative relation between IVOL and risk-adjusted returns in the Swedish stock market is prevalent with the 5-1 strategy producing significant negative alphas in each of our sub-samples. In the 1994-2003 sub-sample, the 5-1 strategy yields an average return of -2.00% and a highly significant alpha of -2.04%. Interestingly, these numbers are much more negative than those for the 2004-2013 sub-sample, during which the 5-1 strategy yields an average return of -1.63% and an alpha of -1.29%, significant at the 5% level.

However, as can be seen in Figure I, the average return of the 5-1 strategy in the 1994-2003 sub-sample is significantly reduced by the extremely negative 5-1 return in the crisis year of 2000. While the 2004-2013 sub-sample has years with large negative average 5-1 returns, it also contains periods of positive average 5-1 returns, which will increase the average 5-1 return over that sample period. Additionally, the periods of positive 5-1 returns in the latter sub-sample will most likely have contributed to the reduced significance and magnitude of the difference in alphas between quintile portfolio 5 and quintile portfolio 1 in the 2004-2013 sub-sample.

When we exclude the crisis years of 2000 and 2008 from the full sample, the average 5-1 return (-1.39%) and alpha (-1.47%) decrease in absolute terms compared to our base case, although the alphas for the 5th quintile and the 5-1 strategy are still highly significant (see Panel C of Table 12). The reason for the decrease in absolute terms can be seen in Figure I, where it is evident that the years excluded are among the top five in terms of most negative average 5-1 return, with year 2000 being the most negative. This finding could be seen as an indication that years of financial turmoil increase the negative relation between IVOL and risk-adjusted returns.

Figure 1

The figure shows the yearly average of the raw monthly percentage returns on the 5-1 strategy.

Table 12

Summary statistics for the use of sub-samples

The time-period studied is the specified sub-period. At the beginning of each month t, we form five portfolios by sorting the sampled stocks on realized idiosyncratic volatility relative to the Fama-French three-factor model over the previous month. We then calculate monthly value-weighted raw and excess returns for the five portfolios, and the difference in the aforementioned returns between quintile 5 and quintile 1. The excess returns are then regressed on the factor returns in the Fama-French three-factor model. Mean reports the average monthly raw percentage return and Alpha reports the alpha in the Fama-French three-factor regression. Robust Huber-White t-statistics are reported in brackets.

Panel A: 1994-2003 sub-period						
	IVOL quintile					
	1	2	3	4	5	5-1
Mean	1.01	1.18	1.26	1.08	-0.98	-2.00
Alpha	0.13	0.13	0.29	0.13	-1.90	-2.04
	[0.55]	[0.45]	[0.55]	[0.25]	[-3.07]	[-2.87]

Panel B: 2004-2013 sub-period						
	IVOL quintile					
	1	2	3	4	5	5-1
Mean	0.99	1.21	1.03	0.66	-0.64	-1.63
Alpha	0.22	0.41	0.22	-0.17	-1.07	-1.29
	[2.14]	[1.84]	[0.95]	[-0.37]	[-1.71]	[-1.98]

Panel C: Base case excluding crisis years						
	IVOL quintile					
	1	2	3	4	5	5-1
Mean	1.37	1.67	1.54	1.44	-0.02	-1.39
Alpha	0.18	0.31	0.24	-0.12	-1.29	-1.47
	[1.34]	[1.78]	[0.78]	[-0.34]	[-2.65]	[-2.81]

4.4 Robustness of findings

In Table 13, we provide a summary of all controls and alterations made to the base case portfolio approach to assess the drivers and the robustness of our findings.

We find a significant negative relation between IVOL and risk-adjusted returns in the Swedish stock market. The finding is robust to controls for size, BtM, turnover, and momentum. The finding is also robust to expanding the IVOL estimation period to 3, 6, 12, and 24 months using daily returns, and to 24 to 60 months using monthly returns. The finding is not robust to employing an equal weighting scheme for all stocks in the Swedish stock market, but after a separate exclusion of January months and microcap stocks, the negative relation is significant for both the equal- and value-weighted portfolio approaches.

Table 13

Summary of controls and alterations made to base case portfolio approach

Control reports the control or alteration made to the base case approach, Mean reports the average monthly raw percentage return of the 5-1 strategy, Alpha reports monthly alpha in percentage terms with respect to the Fama-French three-factor model for the 5-1 strategy. Robust Huber-White t-statistics are reported in brackets.

Control	**Mean**	**Alpha**
Firm characteristic control		
Averaging over Size portfolios	-1.26	-1.25
		[-3.74]
Averaging over BtM portfolios	-1.39	-1.18
		[-3.06]
Market anomaly control		
Averaging over Turnover portfolios	-1.26	-1.06
		[-2.79]
Averaging over Momentum portfolios	-1.58	-1.31
		[-3.65]
Different IVOL estimation periods		
3-month IVOL estimation (daily returns)	-2.05	-1.75
		[-3.32]
6-month IVOL estimation (daily returns)	-2.11	-1.80
		[-3.69]
12-month IVOL estimation (daily returns)	-2.00	-1.74
		[-3.65]
24-month IVOL estimation (daily returns)	-1.93	-1.65
		[-3.31]
24- to 60-month IVOL estimation (monthly returns)	-1.28	-1.04
		[-2.21]
Alternate portfolio weighting scheme		
Equal-weighted portfolios	-0.10	0.16
		[0.30]
January and microcap exclusions		
Excluding January (value-weighted portfolios)	-2.41	-1.71
		[-3.32]
Excluding January (equal-weighted portfolios)	-1.57	-0.93
		[-2.25]
Excluding microcaps (value-weighted portfolios)	-0.66	-0.68
		[-1.73]
Excluding microcaps (equal-weighted portfolios)	-1.47	-1.28
		[-4.33]
Sub-sampling		
1994-2003	-2.00	-2.04
		[-2.87]
2004-2013	-1.63	-1.29
		[-1.98]
Excluding crisis years (2000 and 2008)	-1.39	-1.47
		[-2.81]

4.5 Limitations of research

This section serves to discuss the limitations of the methodology employed in this study. The following aspects are considered to be of great importance: the estimation of idiosyncratic volatility, the choice of asset pricing model, sample inconsistencies, the re-balancing of daily returns in the FF-3F model, the definition of microcap stocks, the absence of additional controls, and the nature of the benchmark index.

4.5.1 Estimation of idiosyncratic volatility

This study only employs the approach of Ang et al. (2006), and measures IVOL relative to the FF-3F model. While other research, such as Fu (2009), has employed an EGARCH approach to measure IVOL, we choose not to. The reason for this is that the EGARCH approach has been criticized for introducing a look-ahead bias (Guo, Kassa, and Ferguson, 2014). Additionally, as mentioned by Stambaugh, Yu, and Yuan (forthcoming), Jin (2013) compares various IVOL estimation methods and finds that past realized volatility, which is the approach employed by Ang et al. (2006) and thereby also the approach employed in this study, outperforms GARCH and EGARCH methods.

4.5.2 Choice of asset pricing model

While the FF-3F model has been found superior to the CAPM in explaining returns, other models such as the Carhart four-factor model have in turn been found superior to the FF-3F model (Carhart, 1997). Our choice of the FF-3F model is based on the approach of Ang et al. (2006) and the subsequent literature on the relation between idiosyncratic volatility and returns, and while it is possible that measuring IVOL relative to the Carhart four-factor model would yield different results, those results would not be comparable to previous research.

4.5.3 Sample inconsistencies

While the Finbas database contains adjusted daily price data for all stocks listed on Swedish lists, it only contains monthly market values for the stocks. It also does not contain the daily number of shares or daily unadjusted closing prices for each stock on the Swedish lists, meaning that it does not provide sufficient information to calculate daily market values.

Additionally, the Finbas database misses market values of shares outstanding for some stocks in some months and book values of equity for some firms in some years. The missing monthly market values (about 4.5% of all monthly observations) mean that all stocks are not consistently included in the Ang et al. (2006) portfolio approach. While we have been able to obtain some of the missing yearly book values of equity, about 9.6% of them are still missing, meaning that not all stocks are consistently included in the FF-3F model factor return calculations.

4.5.4 Fama-French three-factor returns: value weighting of daily returns

Given the lack of daily market values in our dataset, we are forced to rebalance the portfolios in the FF-3F returns calculations on a monthly basis. It is possible that having daily market values and rebalancing on a daily basis could have yielded different results.

4.5.5 Microcap definition

We define microcap stocks using the SEC definition in order to obtain monthly microcap fractions for the Swedish stock market that are more equivalent to the microcap fractions produced for the U.S. by the approach of Fama and French (2008). An alternative approach would be to use the average microcap fraction of 47% of all stocks reported by Chen et al. (2012), and in each month exclude the lower 47% of stocks sorted on market value. However, that would cause the fraction of microcap stocks to be static. Ng and Wang (2004) show that over time, the number of NYSE, AMEX, and NASDAQ stocks in the U.S. stock market with a market value lower than the 20th percentile of market values for NYSE stocks (i.e. the microcap breakpoint used by Fama and French (2008)) has increased substantially more than the number of stocks with a market value in the upper 80% of the market values for NYSE stocks. This means that a static microcap fraction would not appropriately reflect the dynamics of the stock market.

4.5.6 Additional controls

In addition to size, BtM, turnover, and momentum, Ang et al. (2006) also control their finding of a negative relation between IVOL and returns for factors such as leverage, liquidity risk, dollar volume, bid-ask spreads, and dispersion in analysts' forecasts. Because of us not having access to the data needed via Finbas, we have not been able to perform these controls. However, given the findings of Ang et al. (2006), it is unlikely that those controls would significantly change our overall findings.

4.5.7 Nature of the benchmark index used

We have used the OMXSPI as our proxy for the market portfolio. The OMXSPI is the price index version of the Stockholm all-share index, while our stock returns are calculated as gross returns. This means that there is an inconsistency in the returns on the individual stocks relative to the returns on the benchmark index. We opt for the price index version of the Stockholm all-share index because the gross index version (OMXSGI) does not cover the full time-period examined in this study, and there is no other comparable gross return index available for the time-period examined.

5 Conclusions

The purpose of this study has been to examine the relationship between idiosyncratic volatility and returns in the Swedish stock market.

Using the methodology of Ang et al. (2006) and a sample consistently containing nearly all Swedish listed stocks, we show that there is a significant negative relation between idiosyncratic volatility and risk-adjusted returns in the Swedish stock market. A zero-cost portfolio that is long a value-weighted portfolio consisting of stocks in the highest quintile of idiosyncratic volatility and short a value-weighted portfolio consisting of stocks in the lowest quintile of idiosyncratic volatility yields a significant negative risk-adjusted return. The negative relation is robust when controlling for size, book-to-market, turnover, and momentum, and also when expanding the idiosyncratic volatility estimation period to 3, 6, 12, and 24 months using daily returns and 24 to 60 months using monthly returns, confirming the findings of Ang et al. (2009) and Bali and Cakici (2008). The relation is also robust when using sub-periods.

However, when equal weights are assigned to the stocks in the quintile portfolios the negative relation ceases to exist, confirming the findings of Bali and Cakici (2008). In line with the findings of Peterson and Smedema (2011), the negative relation between idiosyncratic volatility and risk-adjusted returns reemerges for the equal-weighted portfolio approach and remains for the value-weighted when January months are excluded. Our findings also support those of Chen et al. (2012), since excluding microcap stocks causes the negative relation between idiosyncratic volatility and risk-adjusted returns to reemerge for the equal-weighted portfolio approach and remain for the value-weighted.

From this, we can conclude that for the non-microcap part of the Swedish stock market, there is a negative relation between idiosyncratic volatility and risk-adjusted returns. For the Swedish stock market overall, there is a negative relation between idiosyncratic volatility and risk-adjusted returns between February and December months.

Our findings contradict and challenge classic financial theory (Markowitz, 1952 and the CAPM framework), suggesting no compensation for holding idiosyncratic risk, as well as alternative theories proposing a positive relation from not being able to fully diversify (Levy, 1978 and Merton, 1987).

Furthermore, the finding that a zero-cost portfolio that is long stocks with high idiosyncratic volatility and short stocks with low idiosyncratic volatility produces significant negative risk-adjusted returns challenges the efficiency of the Swedish stock market. This puzzling finding also indicates that there is a possibility to realize positive returns by going long stocks with low idiosyncratic volatility and short stocks with high idiosyncratic volatility in the Swedish stock market, not considering transaction costs and other costs.

6 Suggestions for future research

To our knowledge, this study is the first that examines and confirms the finding of an anomalous relation between idiosyncratic risk and returns specifically in the Swedish stock market. The natural next step is to explain the anomalous relation. As of now, Stambaugh, Yu, and Yuan (forthcoming) provide the most comprehensive explanation; that many investors purchase stocks but are reluctant or unable to sell short. They also challenge previously proposed explanations, such as that of Bali, Cakici, and Whitelaw (2011). Given the findings of Stambaugh, Yu, and Yuan (forthcoming), it would be interesting and highly relevant to examine if arbitrage asymmetry can explain the negative relation also in a smaller non-U.S. market such as the Swedish.

Additionally, our findings show a reduction in the negativity and statistical significance of the relation between idiosyncratic volatility and risk-adjusted returns for the latter of our sub-samples (2004 to 2013). It would be interesting to examine if this is also the case in other markets, and to revisit the relation between idiosyncratic volatility and returns in the future to investigate if this trend is continuing, and if that is the case, what causes it to do so.

Finally, the finding of an anomalous relation between idiosyncratic volatility and returns also opens up for other future research. As previous documented anomalies such as size, book-to-market, and momentum have been found to be risk factors that enhance the explanatory power of existing asset pricing models, it would be relevant to investigate if the idiosyncratic volatility anomaly could also be one such risk factor. This could be investigated by augmenting asset pricing models such as the Fama-French three-factor (Fama and French, 1993) and the Carhart four-factor (Carhart, 1997) models with a factor incorporating idiosyncratic volatility.

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