Erasmus Research Institute of Management

MPhil Thesis

Does Idiosyncratic Industry Volatility matter?

An investigation of the industry-specific volatility
for the cross-section of the U. S. stock returns

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Date:	30 August 2016

Abstract

The thesis investigates whether industry volatility is priced for the cross-section of stock returns. I explore three main dimensions of industry volatility, the average industry volatility as a factor and the idiosyncratic industry volatility as a factor and as a characteristic. I construct the volatility variables by decomposing the volatility of stock returns following Campbell, Lettau, Malkiel and Xu (2001) to three levels: to market-, industry-, and firm-specific volatility. I test the pricing of industry volatility augmenting the baseline CAPM and Fama and French three- and five-factor models with the industry volatility series and conducting Fama-MacBeth cross-sectional regression analyses. I use three industry classifications, two based on SIC codes, forming 49 (Fama and French (1997)) and 10 industries and one based on FIC codes of Hoberg and Philips (2010) forming 25 industries. I find that the magnitude of idiosyncratic industry volatility could be priced as a characteristic for the cross-section of stock returns, but only for the SIC-code based classifications. Nevertheless, this result does not hold when I require a larger amount of months as a minimum requirement for including a stock in the regression dataset, suggesting sensitivity of idiosyncratic industry volatility to survivorship bias. In addition, I find that none of the baseline models can price spread portfolios formed by ranking stocks based on their idiosyncratic industry volatility and they are mispriced with an alpha of approximately -0.5 to -0.4%. Last, I find that results on the pricing of the three dimensions of industry volatility differs among the three different industry classifications. Hence, I argue that studies related to the pricing of industry idiosyncratic volatility should explore the robustness of their results considering different industry classifications.

Contents

1 Introduction

Merton (1987) postulates that stocks with high idiosyncratic volatility (uncertainty) should have a premium which compensates investors for not holding a fully diversified portfolio. Campbell, Lettau, Malkiel and Xu (2001) decompose the volatility of each stock to three levels: to market-, industry-, and firm-specific volatility. Since then, studies have examined all these three components, however, the pricing of them has only concerned the market- (e.g. Adrian and Rosenberg (2008)) or the firm-specific volatility (e.g. Ang, Hodrick, Xing, and Zhang (2006)). The thesis aims to fill this research gap and investigates whether there is a risk premium for industry-specific volatility, that is, whether investors demand a reward for industry-specific (or idiosyncratic) volatility for the U.S. stock market.

There are several potential reasons for why investors might care about industry-specific volatility. Investors with specialised knowledge on specific industries, like institutional investors, can choose to invest in stocks of specific industries, deciding not to hold a fully diversified portfolio. Such investors can be households and retail investors with connections to companies in specific industries, perhaps because they work there. In this sense, an aircraft pilot or a frequent traveller might have a better understanding of the aviation industry than of the biotechnology or jewellery industry. Hence, such investors might know if there are specific risk factors that influence particular industries. Moreover, investing in industries might also be driven by articles and news in the press (MarketWatch (2015), US News (2014), CNBC (2015), Wall Street Journal (2010)) or industry analyses (e.g. The Economist Intelligence Unit (2016)). There are also fund managers who choose to concentrate only on some industries (Kacperczyk, Sialm and Zheng (2005)). Thus, there exist investors with industry-concentrated portfolios who pay special attention to news affecting particular industries influencing their volatility.

Furthermore, Exchange-Traded Funds (ETFs) have seen an impressive 40% annual growth rate (Massa, Zhang and Zhang (2015) and Wall Street Journal (2015)) with cash flows rivalling actively managed mutual funds (The Economist (2014)). Currently, there are 273 sector US ETFs out of the 613 that concern US stocks (ETFReference.com (2016)) and 997 sector mutual funds out of the 9548 mutual funds (FundReference.com (2016)). Hence, there is another reason to believe that there exist not well-diversified portfolios, concentrated in industries.

Thus far, I have explained that there are investors who hold industry-concentrated portfolios, and according to the theory, investors should be compensated for holding such undiversified portfolios. This fact justifies the concern that the uncertainty of industry sectors, which is reflected in the stock prices by their industry volatility, could influence the stocks' returns. The thesis investigates this concern by asking the main research question of whether industry volatility matters for the cross-section of the U. S. stock returns.

Specifically, the thesis investigates whether the idiosyncratic (individual) industry volatility is priced for the cross-section of stock returns. I explore three main dimensions of industry volatility, the average industry volatility as a factor and the idiosyncratic industry volatility as a factor and as a characteristic. I follow Campbell et al. (2001) and I classify the U.S. stock market to 49 industries based on their SIC classification. Moreover, I proxy idiosyncratic industry volatility, also following Campbell et al. (2001), who use the indirect method of decomposing the volatility of stock returns to market-wide, industry- and stock-level components. Then, I conduct Fama-MacBeth cross-sectional regression analyses using individual stocks as basis assets. I test the pricing of industry volatility augmenting the CAPM and Fama and French (1993, 2015) three- and five-factor baseline models with the respective factor sensitivities of the constructed volatility series.

I find that the factor sensitivity (beta) of the average industry volatility could be priced for the cross-section of stock returns when I assign the stocks to 49 SIC-based industries. However, this result is not robust when I control for size and market volatility beta or consider two additional industry classifications. Furthermore, I find that the factor loadings of the idiosyncratic (individual) industry are not priced as an industry-varying risk factor for the cross-section of stock returns. Moreover, there seems to be a confounding relationship between the idiosyncratic industry volatility and the average idiosyncratic stock volatility within each industry.

Next, I study the idiosyncratic industry volatility as characteristic. I perform Fama-MacBeth cross-sectional regression analysis and I find that idiosyncratic industry volatility is priced as a characteristic. This result is robust when I form quintile portfolios sorting the stocks on their idiosyncratic (individual) industry volatility, adapting the work of Ang et al. (2006) for the idiosyncratic stock volatility to the industry level. I perform two robustness checks; first, by calculating the idiosyncratic industry volatility with the indirect decomposition method, and second, with the direct. I find that the CAPM and Fama and French three- and five-factor models cannot price the spread portfolios of the quintile portfolios, since they produce a statistically significant alpha between approximately -0.5 to -0.4%. This finding should be further examined, since it suggests market inefficiency, because there could exist an investor who sells the spread portfolios in order to earn 0.4 to 0.5% abnormal returns.

However, I find that the pricing of the magnitude of idiosyncratic industry volatility is sensitive to the minimum month requirement in implementing the Fama-MacBeth procedure. In addition, when I require stocks with at least 48 months instead of 24 in implementing the Fama-MacBeth procedure, there is no statistically significant relation between the magnitude of idiosyncratic industry volatility and the cross-section of stock returns. Thus, I argue, that idiosyncratic industry volatility could be priced as a characteristic but it could be subject to survivorship bias.

Last, in order to examine the robustness of the results I consider two different industry classifications. First, I consider a SIC-based classification of a higher level of coarseness, forming only 10 industry divisions instead of the aforementioned 49 industries. Second, I also consider a classification based on the Fixed Industry Classification (FIC) scheme of Hoberg and Philips (2010), who construct it by textually studying the activity description from the 10-K reports of each firm, forming industry classifications of different coarseness. For the thesis, I use the FIC-based classification of 25 industries. My results indicate that they are, in general, robust when I consider the two SIC-based classifications, but not when I consider the FIC-based classification. However, I do not examine the potential selection bias by using the FIC-based industry classification scheme. Thus, I argue that studying multiple industry classifications is important for drawing robust conclusions on industry-level analyses.

Concluding, the thesis makes two main contributions. First, I find that the idiosyncratic industry volatility could be priced as a characteristic. Hence, investors who would like to explain the stock returns should also consider the influence of the idiosyncratic industry volatility when forming their investment portfolios. Second, I contribute to the literature that studies industry-related phenomena by showing that considering different industry classification might yield different results. To the best of my knowledge, there is no asset-pricing related study which studies multiple industry classifications. Hence, researchers investigating such industry-related phenomena, at least for industry-volatility analyses, could perhaps verify the robustness of the results by considering different industry classifications.

The thesis is structured as follows. Section 2 briefly reviews the literature which relates the market and the stock idiosyncratic volatility to the stock returns. It concludes with a discussion of literature on industry volatility. Section 3 develops the hypotheses of the main part of the theses. Section 4 exposes the main methodologies of the thesis and Section 5 describes the dataset construction. Section 6 presents the empirical results. Section 7 further proceeds with robustness checks. Last, Section 8 concludes, discusses the limitations of the thesis and provides insights for further research.

2 Literature Review

The thesis is primarily related to the large literature of studies on stock volatility and I begin the literature review by briefly discussing studies on stock volatility. I continue with a brief discussion of the literature on market volatility. Next, I conclude the literature review with studies on industry volatility; however, to the best of my knowledge there are no studies exploring the pricing of industry volatility.

2.1 Previous research on idiosyncratic stock volatility

Many studies have examined firm-specific idiosyncratic volatility. Nevertheless, the literature is inconclusive on the pricing of stock volatility and the results are mixed. One strand of literature shows that there is a positive relation between stock idiosyncratic volatility and returns, a second strand shows that there is a negative relation and a third strand disputes whether there is a consistent relation.

Fu (2009) and Goyal and Santa-Clara (2003) reflect the first strand and document a positive relation between the lagged average idiosyncratic volatility and the U.S. stock market return during 1962–1999. They find that the lagged average stock variance is positively related to the market return. However, they do not find a significant relation between the lagged market variance and the market return. On the contrary, the second strand is supported by studies like of Diether, Malloy and Scherbina (2002), Easley, Hvidkjaer, O'Hara (2002), Guo and Savickas (2005) and Ang, Hodrick, Xing, and Zhang (2006, 2009) who find that firm-level idiosyncratic volatility is puzzlingly negatively priced as characteristic. Ant eg al. (2006) proxy idiosyncratic stock volatility as the square root of the monthly variance of the residuals in relation to the Fama-French three-factor model and find that neither CAPM nor the Fama-French three-factor model can price portfolios constructed by ranking the stocks based on their idiosyncratic volatility. They also find that stocks with high sensitivities to the first differences or innovations in aggregate volatility, as proxied by the VIX index, have low average returns. Hence, they argue that aggregate volatility risk could be a new cross-sectional and systematic risk factor.

On the other hand, there is also the third strand of literature which consists of critical and sceptical studies on the pricing of firm-level idiosyncratic volatility. For example, Duffee (1995) experiments with different frequency of volatility and returns; he finds a negative relation between stock volatility and returns using monthly data, but positive using daily frequency. Bali, Cakici, Yan and Zhang (2005) dispute the result of Goyal and Santa-Clara (2003). They claim that it is due to small stocks traded on Nasdaq and is partially driven by a liquidity premium. Moreover, extending the sample period of Goyal and Santa-Clara (2003) by only two years and excluding Nasdaq stocks, they find that the result of Goyal and Santa-Clara does not hold. Bali and Cakici (2008) demonstrate that there might be no significant relation between the cross-section of expected returns and idiosyncratic risk when different methodologies such as data frequency of the volatility measures or different data screening are performed. Huang, Liu, Rhee and Zhang (2010) confirm that data frequency plays indeed an important role and they also demonstrate that when return reversal (the phenomenon of the negative cross-sectional relation between stock returns of one period to returns of recent past periods) is controlled there is no negative relation between expected stock returns and idiosyncratic risk.

Moreover, Fu (2009) directly opposes the finding of Ang, et al. (2006). Using exponential GARCH models he finds a positive and not negative relation between the expected returns and the conditional idiosyncratic volatility. Chen and Petkova (2012) argue that the puzzling result of Ang et al. (2006) is driven by a missing risk factor in the model that is used to calculate the idiosyncratic volatility, the Fama and French three-factor model, and indicate that for the cross-section of stock returns, this missing factor is the innovations in average stock variance. Finally, Hou and Loh (2015) collect explanations for the puzzling phenomenon of the negative relationship between stock idiosyncratic volatility and stock returns into three groups and design a unique methodology for examining it. They find that a considerable amount of the puzzle (46%-71%) for the idiosyncratic stock volatility remains unexplained.

To conclude, the methodology differs among the papers which establish a negative or positive relation and it is rarely the case that two papers implement exactly the same methodology, in order to produce directly comparable results. This fact could potentially explain the controversial findings of the different strands of the literature on idiosyncratic stock volatility.

2.2 Previous research on market volatility

I continue the literature review discussing the main findings of the literature which examines the relation of the stock returns to the market volatility. Research in exploring the relation between the expected returns of the aggregate stock market volatility and its risk (variance) is mainly divided into three main strands.

First, there is the strand of literature that finds a negative relation. Such studies include Cremers, Halling and Weinbaum (2015) and Glosten, Jagannathan and Runkle (1983). For example, Glosten et al. use a GARCH-M model to estimate an ex-ante measure of volatility and find a negative relation between the monthly market return and its conditional variance. In addition, Brandt and Kang (2004) find a negative relation between the monthly market return and its conditional variance. However, they find a positive relation to its unconditional variance and they partially argue that this might be the reason for the debate on the sign of the market volatility with respect to the market returns.

Second, there is the strand of literature that finds a clear positive relation. Ghysels, Santa-Clara and Valkanov (2005) introduce the mixed data sample (MIDAS) estimator and find a positive relation between the conditional variance of the stock market return and the conditional mean of the stock market return. Jiang and Lee (2014) confirm Ghysels et al. (2005). They explain that the methodology of previous research does not clearly use the same information set on calculating the stock market return and its variance, and they use a bivariate model of excess returns and their variances which uses a common information set for calculating the two variables.

Third, there are also studies which do not find a clar relation between aggregate market volatility and stock returns. For example, Grullon, Lyandres and Zhdanov (2012), argue that the negative relation of the aggregate market volatility to the stock returns may be due misspecified modelling. When they control for aggregate mactor factors, like aggregate market returns, and the size and value factors of the Fama and French (1993) three-factor model, the aggregate market volatility becomes independent to the stock returns. Moreover, Labidi and Yaakoubi (2016), under a behavioural perspective, find a negative relation between aggregate volatility risk and stock returns when the period under examination is characterised by low investor sentiment, but no relation when the investor sentiment is high.

Hence, as on the studies on idiosyncratic stock volatility, there is also a debate and conflicting evidence on the sign of this relation. Moreover, there is also the possibility that the same result can be interpreted in different ways. For example, French, Schwert, and Stambaugh (1987) find a positive relation between the expected risk premium and the predictable level of volatility. However, the relation is strongly negative between the unpredictable component of the stock market volatility and the excess market returns. Guo and Whitelaw (2006, pp. 1433–1434) interpret the finding of French et al. (1987) as a positive relation between the conditional excess market return and its conditional variance, while Glosten, Jagannathan and Runkle (1983, p. 1780) as a negative relation. In the next subsection, I discuss previous research on industry volatility.

2.3 Previous research on industry volatility

Considering events that influence specific sectors (the dot-com bubble of the information technology industry during 1997–2000, the recent real-estate and finance sector driven financial crisis of 2007-2008, and the oil price plunge after mid-2014) industry-specific volatility has received remarkably little attention, compared to the market and stock volatility, and, in general, the literature suggests that its importance varies over-time.

To the best of my knowledge, no study has investigated the thesis' research question, of whether industry volatility is priced for the stock returns. While there is interest in describing industry-specific volatility, its trends and inter-industry relations, there has been no attempt to identify if industry-specific volatility is priced and the thesis aims to fill this research gap. Studies that examine industry volatility include Wang (2010), Lee, Elkassabgi and Hsieh (2014) and Moshirian and Wu (2009). Wang (2010) finds that volatility shocks in the industries of business supplies, machinery, and consumer goods causally affect the volatilities of most other industries, while other industries like petroleum/natural gas and automobiles/trucks do not affect them. Moreover, Wang (2010) finds linear trends in industry-specific volatilities for 17 out of the 30 industries for the U. S. market. Lee, Elkassabgi and Hsieh (2014) find that the volatility of the utilities industry Granger-causes the volatility of seven out of the nine other industries they examine. They claim that this finding is supported by the investor sentiment that "old economy" stocks are more easily risk assessed. They claim that the volatility of the utilities industry is important for the majority of the other industries they study. Moshirian and Wu (2009) examine 36 developed and emerging markets from 1980 to 2001 and find that banking industry volatility can predict systemic banking crises in developed markets, but not in emerging markets. Hence, there is a reason to believe that industry-specific idiosyncratic volatility is important for the banking industry from a crisis perspective.

As explained in the introduction, the thesis' research question is justified by investors and researchers who believe that it is better to concentrate and diversify within industries. Consequently, they hold less diversified portfolios which are more prone to the effects of industry volatility, suggesting exposure to industry related volatility. Herewith, I expose the relevant literature which is mainly macroscopically divided into two strands. The first strand argues that international diversification is favored compared to industry diversification. The second strand, claims the opposite. Hence, if investors follow the second strand, they will concentrate their investments to stocks in specific industries, and potentially be subject to idiosyncratic industry risk.

Research similar to Heston and Rouwenhorst (1994) and Griffin and Karolyi (1998), reflect the first strand. For example, Heston and Rouwenhorst (1994) study 12 European countries during 1978–1992 and decompose volatility to pure country and industry sources of variation. They show that country return volatility is minimally explained by the countries' industrial structure and they propose international diversification within an industry as a more effective way to reduce risk compared to industry diversification within a single country.

On the other hand, the second strand relates to studies like the one of Ferreira and Gama (2005) who extend the Campbell et al. (2001) volatility decomposition internationally, to include stock volatility at the world, country and local (within a country) industry levels. They find that local industry volatility dominates the other volatility measures. They claim that global industry risk has largely increased in comparison with the world market in the 1990s and hence industrial diversification is more efficient than inter-country diversification, in the last years of their 1973–2001 sample. This result is in accordance with Roll (1992) who finds that industry factors explain approximately 40% of stock return variability, using a sample from 1988 to 1991, but is in contrast to Heston and Rouwenhorst (1994).

In addition, more recent studies indicate that portfolios formed by diversifying over industries can be more efficient than portfolios formed by diversifying over countries (Moerman (2008) and Marcelo, Quirós and Martins (2013)). Moerman (2008), using a less restrictive methodology than that of Heston and Rouwenhorst (1994), finds that a pure industry investment strategy offers better diversification opportunities compared to a pure country strategy, for his 1995–2004 European sample. Marcelo, Quirós and Martins (2013) study nine European countries from 1990 to 2008, and classify the stocks into 10 industries. They find that the country effect does not dominate the industry effect with respect to market return variations. They claim that diversifying over industries forms more efficient portfolios. Last, Hiraki, Liu and Wang (2015) study 389 equity funds from 1993 to 2009 and find that industry- and country- concentrated funds perform better than their diversified, not concentrated counterparts.

Apart from the diversification over industries or country controversy for forming efficient portfolios, there could also be other reasons that justify diversification over industries. For example, mutual fund managers may concentrate their holdings in industries for political reasons (Hong and Kostovetsky (2012)) or for better performance, in spite of having a less diversified portfolio (Kacperczyk, Sialm and Zheng (2005)). Kacperczyk et al. show that the expertise of mutual fund managers may be linked to specific industries; when mutual funds are concentrated in specific industries, they have better performance than well-diversified mutual funds. Furthermore, Fedenia, Shafer and Skiba (2013) construct several industry concentration measures and find that "industry-concentrated portfolios of foreign and U. S. institutional investors outperform [return-wise] more diversified portfolios for the U. S. securities during 2000–2009."

Last, the study of industry related factors in asset pricing, although it seems more widespread in practice, is minimal in academic research. Chou, Ho and Ko (2012) use principal component analysis and examine returns of industry portfolios. From the last two factors extracted from five principal components, they construct two risk industry-based factors, but their explanatory strength seems weak when they control for size, value and momentum.

To conclude the literature review, the research of the risk-return relationship from the perspectives of the market volatility and idiosyncratic stock volatility has produced mixed results in the literature and there is no a crystal clear empirical relation. Moreover, the relation of the industry volatility to the stock returns, although justified intuitively given the findings of previous industry related studies, has not been examined, to the best of my knowledge. In the following section, I form the main hypotheses of the thesis.

3 Hypothesis Development

3.1 The pricing of average industry volatility

Intuitively, an investor can perceive the stock market as one entity, in which case he perceives the uncertainty of the market's return as a whole and this uncertainty can be proxied by the volatility of the market returns, which I calculate following Campbell et al. (2001). I describe its calculation in the methodology section of the thesis. On the other hand, from a microscopic perspective, an investor can consider the uncertainty of each stock return, which can be measured with a measure of idiosyncratic stock volatility. Hence, apart from the aggregate market volatility, an investor can consider idiosyncratic stock volatility at an aggregate level, the average firm volatility among all stocks. I also follow Campbell et al. methodology in calculating it.

At a meso-level, groups of firms which roughly specialise in the same area of activities, producing homogenous products, form industries or sectors. Investors may perceive the average industry volatility among all industries, that is, the industry volatility, at an aggregate level, as a risk factor. For example, there might be periods of low uncertainty in the industries, but other periods of high uncertainty in industry returns, like the uncertainty in the industry returns, which started from the financial and real-estate sectors, during the financial crisis of 2007–2008.

Moreover, the uncertainty in stock returns of specific industries is not necessarily isolated from the uncertainty of the stock returns of other industries. Intuitively, the uncertainty in the industry of electronic equipment is not isolated from the uncertainty in the computers industry. For example, Menzly and Ozbas (2010) present evidence that the returns of individual firms and across industries are cross-predictable based on the firms' supplier-customer linked industries. Thus, investors who choose to concentrate their portfolio on specific industries, as explained before, should also be interested in other industries due to their economic relations. Hence, investors assessing the investment opportunities may not only take into account the individual industry volatility for the industries of their concern, but also, at an aggregate level, investors can perceive the average industry volatility of every industry in the market as a risk factor. In the thesis, I also following Campbell et al. (2001) to calculate the average industry volatility.

As described above, the theory is different than practice on the sign of the relation between volatility and stock returns. A strand of literature has shown that there is a negative relation between idiosyncratic volatility and stock returns, but according to Merton (1987), the sign of this relationship should be positive. Moreover, previous study has not examined, to the best of my knowledge, the relationship between average industry volatility and stock returns, and I conjecture that there is such a relationship and stock returns should be priced relative to their sensitivity to average industry volatility. Thus, I form *Hypothesis 1* and I hypothesise that *stock returns are not related to their sensitivity to average industry volatility.*

3.2 The pricing of idiosyncratic industry volatility

A strand of literature (including Ang et al. (2006)) has shown that stock idiosyncratic volatility is priced as characteristic. However, to the best of my knowledge, there is no study that separates the pricing of stock-level idiosyncratic volatility with the pricing of industry-level idiosyncratic volatility. Is it only the case that stock idiosyncratic volatility is priced, or is it also that the idiosyncratic industry volatility of a stock is also priced?

I explore two dimensions of the pricing of idiosyncratic industry volatility. First, I consider that stock returns are a function of factor sensitivities (betas or loadings) to their idiosyncratic industry volatility. Hence, I consider idiosyncratic (i.e. individual) industry volatility as an industry-varying factor. Similarly, to hypothesis 1, to the best of my knowledge, there is no study that examines the pricing of idiosyncratic industry volatility as an industry-varying factor and I conjecture that there is such a relationship. Thus, I form *Hypothesis 2* and I hypothesise that *stock returns are not related to their sensitivities to their idiosyncratic industry volatility.*

Second, Daniel and Titman (1997) examine the factor sensitivities and the magnitudes of the variables of size and value and they indicate that stock returns are explained by their characteristics, the magnitudes of value and size, and not by the factor sensitivities to portfolios formed by sorting stocks on size and value. Thus, I also consider the pricing of idiosyncratic industry volatility as characteristic. Similarly to hypotheses 1 and 2, I form *Hypothesis 3* and I hypothesise that *stock returns are not related to the magnitude of their respective idiosyncratic industry volatility.*

3.3 Does industry classification influence the pricing of industry volatility?

The industry classification varies among different studies and settings. For example, studies on volatility like Goyal and Santa-Clara (2003), Wang (2009), Lee, Elkassabgi and Hsieh (2014) classify the U.S. market to 17, 30, 10 different industries, respectively. Ferreira and Gama (2005), in an international setting aggregate 38 industries into 10 economic sectors.

The question, then, arises, whether industry classification matters in drawing robust conclusions. I hypothesise that it should not. To the best of my knowledge, this question has not been examined in the asset pricing literature. There is a minimal number of studies which examine the differences in industry classification schemes from a meta-analysis/documentation (Weiner (2005)) and accounting (Kathleen and Walkling (1996), Bhojraj, Lee and Oler (2003)) perspective. However, to the best of my knowledge, there is no study which explores the differences in asset pricing inference when there are multiple industry classification schemes considered.

In the thesis, I consider three industry classifications. First, I assign the stocks into 49 industries classified by the Standard Industrial Classification (SIC code) as in Fama and French (1997). Second, I assign the stocks into 10 divisions, again based on their SIC code. Third, I assign stocks based on the work of Hoberg and Phillips (2010) into 25 industries according to their Fixed Industry Classification (FIC) data. Since industries are formed by firms which operate in the same area of activities, the pricing of industry volatility should not be affected by considering different industry classifications. I form *Hypothesis 4* and I hypothesise that *the existence or the absence of existence of a pricing relation between the stock returns and the average industry volatility or the idiosyncratic industry volatility holds for different industry classifications.*

In conclusion, I have formed four hypotheses to test whether industry volatility is priced for the cross-section of stock returns. First, I hypothesise that average industry volatility at the aggregate level is not a priced common factor among all stocks. Second, that idiosyncratic industry volatility is not priced as an industry-varying factor, that is, the particular risk factor varies by industry and it is not common for the whole cross-section of stock returns. Third, I hypothesise that idiosyncratic industry volatility is not priced as characteristic for the stock returns. Last, since I examine volatility at an industry level, the pricing of the aforementioned volatility measures should not change if I consider different industry classifications. I continue the thesis by explaining the methodology I follow for testing these hypotheses.

4 Methodology

4.1 Estimation and Inference

Following Cochrane (2005), the volatility series are not traded portfolios and hence I do not perform time-series regression analysis. Second, I examine individual stocks as basis (or test) assets and simple cross-sectional regression analysis is impossible because the covariance matrices require balanced panels. I concentrate on individual stocks because the literature has shown that different portfolios provide different results. For example, Ang, Liu and Schwarz (2008) argue, especially for cross-sectional analyses, that using individual stocks can lead to more efficient tests on the pricing of factors. Moreover, I concentrate on individual stocks, because I notice a trend in the literature which also uses individual stocks instead of portfolio-based analysis, like in Brav, Lehavy and Michaely (2005), Bali, Brown and Caglayan (2012), Bali, Peng, Shen and Tang (2014), and Cremers, Halling and Weinbaum (2015).

Hence, for the analysis I use the two step Fama-MacBeth (1973) cross-sectional procedure with time-varying betas which I implement as follows. First, I estimate the factor sensitivities (betas) using time-series regressions for each individual stock and second, I proceed to the two-step procedure in calculating the cross-sectional risk premia of the independent variables. I use five-year rolling time-windows to estimate the betas and to capture their time-variation. I require for each stock at least 2 years (24 months) of monthly observations.[1]

For simplicity, I describe the Fama-MacBeth (1973) procedure considering the Fama-French (1992) three factor model. Consider I have $i = 1, 2, \ldots, N$ individual stocks during a period of $t = 1, 2, \ldots, T$ months of the dataset, with $t = 1$ the month of July 1963. First, for each time window, I run time-series rolling regressions of the excess returns of each

[1] A minimum of twenty-four months, is a common requirement in the literature for calculating sensible betas, like in Bali, Peng, Shen and Tang (2014, p. 1441). Moreover, for a given month I convert the daily returns (`RET` of the CRSP database) to monthly returns applying calculating R_{monthly} as in

$$R_{month_t} = \left(\prod_{TD=1}^{TD_{\text{last}}} (1 + R_{\text{daily, } TD}) \right) - 1$$

where TD denotes the trading day and TD_{last} the last trading day of the month.

stock, R^e, on the three factors,

$$R^e_{1,t} = \alpha_1 + \beta_{MktRf,1} MktRf_{1,t} + \beta_{SMB,1} SMB_{1,t} + \beta_{HML,1} HML_{1,t} + \epsilon_{1,t} \tag{4.1}$$
$$R^e_{2,t} = \alpha_2 + \beta_{MktRf,2} MktRf_{2,t} + \beta_{SMB,2} SMB_{2,t} + \beta_{HML,2} HML_{2,t} + \epsilon_{2,t} \tag{4.2}$$
$$\vdots$$
$$R^e_{N,t} = \alpha_N + \beta_{MktRf,N} MktRf_{N,t} + \beta_{SMB,N} SMB_{N,t} + \beta_{HML,N} HML_{N,t} + \epsilon_{N,t}, \tag{4.3}$$

for each of the N stocks and I obtain the estimated with the method of ordinary least squares (OLS) betas, $\hat{\beta}$, for each one of the N stocks. Each time-window has a length of 60 months. For each stock, I use the first 60 months to calculate the beta coefficients of the 60th month and I do not assign any beta for the first 59 months of the stock. Subsequently, I remove the first month of the estimation window, add the following month, and I repeat this process to calculate monthly-updated betas, rolling the 60-month time-window over the course of the dataset's history. For the 60-month windows, I require at least 24 months of valid data, not necessarily consecutive.

Second, I run $T-60$ cross-sectional OLS regressions for each period (month),

$$R^e_{t=61,i} = \lambda_{61} + \lambda_{61,MktRf}\hat{\beta}_{60,MktRf,i} + \lambda_{61,SMB}\hat{\beta}_{60,SMB,i} + \lambda_{61,HML}\hat{\beta}_{60,HML,i} + \varepsilon_{61,i}$$
$$R^e_{62,i} = \lambda_{62} + \lambda_{62,MktRf}\hat{\beta}_{61,MktRf,i} + \lambda_{62,SMB}\hat{\beta}_{61,SMB,i} + \lambda_{62,HML}\hat{\beta}_{61,HML,i} + \varepsilon_{62,i}$$
$$\vdots$$
$$R^e_{T,i} = \lambda_{T} + \lambda_{T,MktRf}\hat{\beta}_{T-1,MktRf,i} + \lambda_{T,SMB}\hat{\beta}_{T-1,SMB,i} + \lambda_{T,HML}\hat{\beta}_{T-1,HML,i} + \varepsilon_{T,i},$$

where $R^e_{t,i}$ are the excess returns of every stock in month t. Moreover, in the tests of firm characteristics, I add in the cross-sectional regression specification the corresponding characteristics' variables, which is commonly used in the literature like in Goyal (2012).

The estimated risk premia, $\hat{\lambda}$ in the tables, are calculated averaging the risk premia from the $T-60$ cross-sectional regressions, e.g. $\hat{\lambda}_{\beta_{MktRf}} = \frac{1}{T-60}\sum_{t=61}^{T}\hat{\lambda}_{t,\beta_{MktRf}}$. Hence, I run the time-series regressions covering the period 07:1963–12:2015 and the cross-sectional during 07:1968–12:2015 (570 months).

When there is high first-order autocorrelation in the volatility series, the tables report Newey-West t-statistics for the sample means of the estimated risk premia and are calcu-

[2]Chosen according to Newey and West (1994)), for $273 <= T-60 < 621$ months, $\left\lfloor 4 \cdot \left(\frac{T-60}{100}\right)^{\frac{2}{9}} \right\rfloor = 5$. For the Fama-Macbeth regression analyses using the FIC industry classification, I use 4 lags, because the sample duration is shorter.

lated with a lag of 5.[2] When there is no high first-order autocorrelation in the volatility series, I report the t-statistics calculating the Shanken (1992) correction by multiplying the Fama-MacBeth coefficient standard errors by the adjustment factor as described in Campbell, Lo and MacKinlay (1997, p. 216), $\frac{1+(\hat{\mu}_m - \hat{\gamma}_0)^2}{\hat{\sigma}_m^2}$, where $\hat{\mu}_m$ and $\hat{\sigma}_m^2$ is the mean risk premium and the variance of the factor, respectively, and $\hat{\gamma}_0$ the intercept coefficient from the second step of Fama-MacBeth procedure. As Campbell and MacKinlay (1997) describe, the Shanken correction eliminates the errors-in-variables biases because of the first step, but not the possibility that other variables might enter spuriously the model. In general, the Newey-West standard errors produce more conservative t-statistics than the Shanken-adjusted t-statistics, for the risk premia of the betas of the volatility series, so I omit the Shanken-adjusted t-statistics in the thesis' main tables, but I do include them in the web appendix. Nevertheless, Cochrane (2005) indicates that for datasets with monthly frequency, the multiplicative term of the Shanken-adjustment factor is small and ignoring it makes little different.

The reported coefficients of determination (in the table columns I include R^2 and $R^2 - adj$ in parentheses) are the averages of coefficients of determination of the cross-sectional regressions. An alternative could be calculating a cross-sectional R^2 as in Jagannathan and Wang (1996) and Petkova (2006). Nevertheless, Lewellen and Nagel (2006, p. 310) cautions on its usage and I do not include it. Specifically, Lewellen and Nagel (2006) claim that calculating the cross-sectional R^2 is inappropriate when a study focuses on cross-sectional regressions without conducting time-series intercept tests, as is the case with the thesis, since it focuses on the cross-section of the U. S. stock returns.

4.1.1 Factor models

Since the formalisation of the Arbitrage Pricing Theory by Ross (1976) a plethora of models have been evolved. For example, Fama and French (1993) developed a three factor model including a value and size factor, and Carhart (1997) extended the last to include a momentum factor. In the Fama-MacBeth regression analyses, I use three baseline models: (i) the Capital Asset Pricing Model (CAPM) of Sharpe (1964) which includes only one factor, the excess market return, (ii) the Fama-French (1992) three-factor model (FF3) which includes two additional factors to CAPM, the SMB (small-minus-big) and HML (high-minus-low) factors which correspond to size and value risk factors and are formed by value-weighted portfolios of stocks ranked on capitalisation and the book-to-market ratio, and finally, (iii) the Fama-French (2015) five-factor model (FF5) which further adds two additional factors to the FF3, the RMW (robust-minus-weak) and CMA (conservative-minus-aggressive) factors. RMW, which corresponds to a profitability factor, is calculated as the return difference on diversified portfolios subtracting returns of stocks with weak profitability from returns of stocks with robust profitability. Last, CMA, corresponds to an investment factor and is calculated as the return difference on diversified portfolios subtracting returns of stocks of high investment firms from returns of stocks of low investment firms.

4.1.2 Hypothesis testing

In order to test the hypotheses, I estimate the cross-sectional second step of the Fama-MacBeth procedure that was described previously in Section 4.1 and I present corresponding tables in its section. In the web appendix,[3] I include all the tested specifications, which I do not include in the thesis to preserve space. In this section, I explain how I test the hypotheses of Section 3 and I also introduce the volatility series, which I calculate following the indirect decomposition method of Campbell et al. (2001), as I describe in the Section 4.2 below. The results of these tests are presented in Section 6.

4.1.2.1 Testing hypothesis 1

To test hypothesis 1 of Section 3.1, the pricing of average industry volatility, I augment the three factor models, described previously in Section 4.1.1, with the factor loadings (betas) of each stock to the average industry volatility. I conduct the Fama-MacBeth procedure, described in Section 4.1, and I test the statistical significance of the risk premium of the beta of the average industry volatility with the estimated t-statistics, as calculated from the cross-sectional regressions of the Fama-MacBeth procedure. As proxy for the average industry volatility, I use the variable IND which I calculate following the decomposition method of Campbell et al. (2001) and I describe in the Section 4.2 below. I denote the beta of IND with β_{IND}.

As I overview in the literature review, Section 2, literature has shown that there might be a relation between the stock returns and the market or the idiosyncratic stock-level volatility. In testing the statistical significance of the risk premium of β_{IND}, I control for this relationship by also augmenting the factor models with the betas of the market volatility and idiosyncratic stock volatility, at the aggregate level. Hence, I use the betas

[3] Located at https://github.com/costis-t.

of market-wide (aggregate) volatility measures, MKT, which I denote with β_{MKT}, and the betas of the average firm volatility across all firms for a given month, $FIRM$, which I denote with β_{FIRM}. Thus, if average industry volatility is priced, the risk premium of its beta should be statistically significant for every tested specification.

4.1.2.2 Testing hypothesis 2

To test hypothesis 2 of Section 3.2, the pricing of idiosyncratic industry volatility as factor, I augment the three factor models, with the factor loadings (betas) of each stock to their idiosyncratic industry volatility. Similarly to testing hypothesis 1, I conduct the Fama-MacBeth procedure and I test the statistical significance of the risk premium of the beta of the individual industry volatility with the estimated t-statistic. As proxy for the idiosyncratic industry volatility, I use the variable of idiosyncratic industry volatility, following Campbell et al. (2001), and I denote it with $IIND$. In contrast to SMB, HML and IND which I consider as common risk factor among all stocks, I treat $IIND$ as an industry-varying factor, that is, $IIND$ varies by industry: for a given month stocks within an industry have the same magnitude of $IIND$, but stocks in different industries have different magnitudes of $IIND$. I denote the beta of $IIND$ with β_{IIND}.

I control the relation of β_{IIND} to the stock returns with the beta of the market volatility, β_{MKT}, similarly to testing hypothesis 1. As proxy for the idiosyncratic volatility at an industry level, I use the average idiosyncratic (stock-specific) volatility for stocks within an industry and I calculate following Campbell et al. (2001). I denote this variable with $AIFIRM$, and I also treat it as an industry-varying factor. I denote the beta of $AIFIRM$ with β_{AIFIRM}. I use $AIFIRM$ to proxy idiosyncratic stock-volatility, because it would not be as appropriate to use the aggregate variable $FIRM$, since at an industry level the variable $AIFIRM$ captures more closely the idiosyncratic stock volatility than the average idiosyncratic volatility across all stocks in the market ($FIRM$).

4.1.2.3 Testing hypothesis 3

To test hypothesis 3 of Section 3.2, the pricing of idiosyncratic industry volatiltiy as characteristic, I augment the three factor models, with each stock's idiosyncratic industry volatility, measured by the variable $IIND$, described previously in testing hypothesis 2. I conduct the Fama-MacBeth procedure adding the variable $IIND$ in the second step of the cross-sectional regression of the procedure. As controls, I use the the betas of the variables MKT, IND, and $FIRM$ described previously and moreover the idiosyncratic (stock-level) volatility of each stock, which I denote with the variable $IFIRM$, calculated following Campbell et al. (2001) and is described in Section 4.2 below.

4.1.2.4 Testing hypothesis 4

To test hypothesis 4 of Section 3.3, of whether the pricing relations of hypotheses 1-3 alter by considering different industry classifications, I perform all the aforementioned analyses for the two other industry classifications, also described in Section 3.3. The hypothesis will not be rejected if the industry volatility related pricing relations hold for every industry classifications.

4.1.2.5 Size and Value controls

In the Fama-MacBeth regression analyses, apart from the volatility proxies previously described, I also control for the size and value characteristics, which I calculate following Bali et al. (2016). I calculate size, the market capitalization or equity (ME) from the Compustat/CRSP merged database, multiplying the price and the shares outstanding of the corresponding stock (the fields `prcc_f` and `csho` of the database). As proxy for value, I use the book-to-market ratio as it is also calculated in Bali et al. (2016). Hence, I calculate book value (BE) as in

$$BE = SEQ + TXDB + ITCB - BVPS, \tag{4.4}$$

where `SEQ`, `TXDB`, `ITCB`, and `BVPS` are the book value of stockholder's equity, the tax effects plus the deferred taxes, the investment tax credit and the value of preferred stock, respectively. In order to minimize the bias by extreme values, I use the logarithms of BM and ME.

4.1.3 Economic importance

In order to assess the economic importance of the estimated risk premia from the second step of the Fama-MacBeth procedure, I need to calculate the standard deviation of the betas of the risk factors, which I do in the "Variable descriptive statistics" Table 3 of the empirical results section. To do that, I calculate the factor loading (beta) of each variable in a similar manner to the time-series regressions of the Fama-MacBeth procedure described previously in Section 4.1. For each stock, I average its estimated time-varying betas across time and I assign one such average beta $(\bar{\hat{\beta}})$ for each stock. As I present below, Table 3 contains the descriptive statistics for the aforementioned average betas as well as for the returns and the size and value controls. For example, to calculate the mean of $\bar{\hat{\beta}}_{IND}$ across all stocks, first I run a univariate time-series 60-month rolling regression for each stock

$$XRET_t = \alpha + \beta_{INDvw} INDvw_t + \varepsilon_t. \tag{4.5}$$

Then, I average all the estimated $\hat{\beta}_{IND}$ for each stock. Hence, Table 3 will report the mean of the average $\bar{\hat{\beta}}_{IND}$ across all stocks. This "cross-sectional" methodology differs from calculating the corresponding descriptive statistics table by pooling the corresponding variables, in two ways. First, there are stocks with different length of observations, effectively biasing the corresponding descriptive statistics. Second, by pooling the variables, I would also include a time-series component in the descriptive statistics, while my analysis concerns the cross-section of the stock returns.

4.2 Volatility Decomposition

In this section, I discuss the calculation of the volatility variables described in the Hypothesis Testing Section 4.1.2. Xu and Malkiel (2003) discuss two methods for measuring idiosyncratic volatility: the *indirect* and the *direct decomposition* methods. There is literature that uses the first (Campbell et al. (2001), Brandt, Brav, Graham and Kumar (2010), and Wang (2009)) and others (Bali and Cakici (2008), Fu (2009), Chen and Petkova (2012), Xu and Malkiel (2003)) who use the second or both.

For the main part of the thesis, I use the indirect decomposition method and for robustness of the important results I also use the direct. I closely follow Campbell et al. (2001) and I decompose the stock returns into three components: the market-wide return, and the industry- and firm-specific residuals. I calculate the volatility series in a monthly frequency, using daily data. I index industries and individual stocks by the i and j subscripts respectively. The return of the stock j in industry i in period t is R_{jit} and w_{jit} is the weight of the stock j in industry i in period t. I calculate the return of industry i in period t as

$$R_{it} = \sum_{j \in i, t-1} w_{jit} R_{jit},$$

where R_{jit} is the stock's `RET` field in the CRSP database for each stock, as percentage.

I use the return percentage terms, because the factors in the literature are in percent returns. However, because I measure variance, the use of percentage returns effectively multiplies the originally calculated series of Campbell et al. (2001) by 1×10^4.

I use a value- and an equally-weighted scheme, denoted in the variable name of the volatility series by the subscripts vw and ew respectively. Throughout the thesis, I concentrate on the value-weighting scheme because it represents actual investment returns, but I also present results based on the equally-weighted scheme in the web appendix. I implement the value-weighting scheme following Campbell et al. (2001), and I calculate the weights of the volatility series in month t based on the capitalization of the stocks in month $t-1$. Formally, I calculate w_{jit} as in

$$w_{jit} = \frac{\text{Capitalization}_{d_{ji,t-1}}}{\sum_{j \in i} \text{Capitalization}_{d_{ji,t-1}}},$$

where d_{jit} is the last trading day of stock j in industry i in a given month t. Hence, a stock with no valid price and share data for the month $t-1$ is excluded from calculating the volatility series in month t. The equally-weighting scheme calculates w_{jit} as in

$$w_{jit} = \frac{1}{N_{jt}},$$

where N_{jt} is the number of firms in industry j in period (month) t. To calculate the capitalization, I use the adjusted capitalization[4] formula and the adjustment factors provided by CRSP (Capitalization $\equiv (\texttt{SHROUT} \cdot \texttt{CFACSHR}) \cdot \frac{\texttt{PRC}}{\texttt{CFACPR}}$).[5]

Correspondingly, the weight of industry i in the total market in period t is w_{it} and hence the market return is

$$R_{mt} = \sum_{i,t-1} w_{it} R_{it}.$$

I follow Campbell et al. (2001) to calculate the average industry volatility, IND_t. Defining ϵ_{it} as the difference between the market return R_{mt} and the industry return R_{it},

$$\epsilon_{it} = R_{mt} - R_{it}, \tag{4.6}$$

[4] An alternative would be to calculate the unadjusted capitalization from the product $SHROUT \cdot PRC$. Nevertheless, both formulas return series with an almost perfect correlation of more than 0.99 and in unreported results the figures seem identical and there is no substantial difference in the tables which present the results of the Fama-MacBeth cross-sectional regressions.

[5] In unreported results, apart from the described and the Campbell et al. (2001) weighting schemes,

the estimated volatility of industry i, $\hat{\sigma}^2_{\epsilon it}$, is

$$\hat{\sigma}^2_{\epsilon it} = \sum_{s \in t} \epsilon^2_{is}. \tag{4.7}$$

With the methodology explained in detail in Campbell et al. (2001), the measure for average industry volatility IND_t is calculated by

$$IND_t = \sum_{i} w_{it} \hat{\sigma}^2_{\epsilon it}. \tag{4.8}$$

The market-wide volatility, MKT_t, is calculated as in

$$MKT_t = \hat{\sigma}^2_{mt} = \sum_{s \in t} \left(R_{ms} - \mu_m\right)^2, \tag{4.9}$$

where R_{ms} is the market return of the specific period (month) s and μ_m is the average market return for the whole sample.

For the average firm-specific volatility, $FIRM_t$, Campbell et al. apply the same logic as in the calculation of industry-specific volatility. I define η_{jit} as the difference between the industry return R_{it} and the firm return R_{jit},

$$\eta_{jit} = R_{it} - R_{jit},$$

and the estimated firm-specific volatility of firm j, $\hat{\sigma}^2_{\eta jit}$, is then

$$\hat{\sigma}^2_{\eta jit} = \sum_{s \in t} \eta^2_{jis}. \tag{4.10}$$

The weighted average of the firm-specific volatilities within an industry is

$$\hat{\sigma}^2_{\eta it} = \sum_{j \in i} w_{jit} \hat{\sigma}^2_{\eta jis}. \tag{4.11}$$

I calculate the average firm-specific volatility, $FIRM_t$ averaging over industries,

$$FIRM_t = \sum_{i} w_{it} \hat{\sigma}^2_{\eta it}.$$

For the volatilities of individual industries and firms, which are not averaged across industries, I follow section II.C (p. 20) of Campbell et al. (2001) and I proceed with a decomposition which includes a beta for each individual firm and stock. For comparison purposes with Campbell et al. (2001), I assume that betas are constant over time. I calculate the industry- ($\tilde{\epsilon}_{it}$) and firm-level ($\tilde{\eta}_{jit}$) residuals from the equations

$$R_{it} = \beta_{im} R_{mt} + \tilde{\epsilon}_{it} \tag{4.12}$$

$$R_{jit} = \beta_{im} R_{mt} + \tilde{\epsilon}_{it} + \tilde{\eta}_{jit}. \tag{4.13}$$

Next, I calculate the individual industry volatility ($IIND_t$), the individual firm volatility ($IFIRM_t$) and the average firm volatility within an industry ($AIFIRM_t$) from equations (4.7), (4.10) and (4.11), respectively. I calculate each series with a value- and equally-weighting scheme. Specifically for $IFIRM_t$, I calculate a value- ($IFIRMvw_t$) and equally-weighted variant ($IFIRMew_t$), with respect to the value- and equally-weighted market return in Equation (4.13).

5 Data

My sample consists of all common stocks (i.e. with share code `shrcd` `10` or `11`) listed on NYSE, NYSE MKT and Nasdaq exchanges from the CRSP daily data base.[6] Hence, I exclude American Depositary Receipts (ADRs), Shares of Beneficial Interest (SBIs) and Units. Moreover, I exclude when-issued trading for these stock exchanges (`PERMNO`s with `EXCHCD` 31, 32 or 33). I identify stocks by their `PERMNO` number. The start month is July 1962 because NYSE MKT starts its operations then (on July 2, 1962[7]) and also for comparison purposes with Campbell et al. (2001) who start their sample then. The ending month is December 2015 (December 31, 2015). Following Campbell et al. (2001), I consider stocks not assigned by Fama and French (1997) to an industry as an additional industry, named “Unclassified”. Hence the total number of industries is 49.[8]

I require valid price, return, share and industry classification (SIC code) data. I arrive at 1,963 common stocks in July 1962 and 3,794 in December 2015. Following Campbell et al. (2001) and for comparison purposes, I do not do any further screening in constructing

I have experimented with different schemes. They all produced highly correlated volatility series with correlations ranged from 0.9931 to more than 0.9999.

[6] The 07:1962–12:2015 raw data set I download from the CRSP/WRDS web interface from consists of 80,635,603 daily observations for 30,789 different `PERMNO`s.

[7] No stock is traded on July 1, 1962.

[8] Note that before July 1962 there are only 44 SIC classified Industries while after July 1962, 48. Moreover, before September 1968 there is no “Healthcare” industry in the sample.

the volatility series and I reach a data set with 61,280,215 daily (2,939,730 monthly) observations and 23,609 unique stocks. For the Fama-MacBeth regression analyses, as explained above, I use the Fama and French (2015) five-factor model, who calculate the factors of RMW and CMA only after July 1963, inclusive, and hence I reach a dataset with $2,916,021$ monthly observations and $23,541$ unique stocks.

In Table 1, I present stock-wise summary statistics for the resulting dataset. The minimum monthly return of more than -90% in absolute value may seem surprisingly low, but I cross-check with the Bloomberg database that it is not a data error for a couple of cases and I assume it is not an error for the rest. For example, for the Financial sector the stock of Lehman Brothers (`PERMNO` 80599) experiences a more than 99% drop in September 2008 and for the Drugs industry in February 2009 La Jolla Pharmaceutical (`PERMNO` 80640) had a very large drop because its major owner Gonzales Alejandro, sold around 6% of the firm's shares at a very low price. For the other side of the maximum monthly return, in the Steel Industry, Metallurgical Industries Inc, (`PERMNO` 53154), gradually climbed from \$0.03125 to \$0.625 in August 1993, resulting in a monthly return of +1900%.

Moreover, I retrieve factor data and the risk-free rate from Kenneth French data library. In the thesis I control for book-to-market ratio and market equity which requires merging with the CRSP with the CRSP/Compustat Merged (CCM) annual database. The CCM database with complete and valid data for the book-to-market ratio and market equity for 07:1963–12:2015 corresponds to 21,643 different stocks and 2,665,294 monthly observations. Merging it with the CRSP dataset, I reach 2,077,886 monthly observations and 17,849 `PERMNO`. I lose around 29.0% monthly observations and 24.2% `PERMNO`s, so I decide to create different panels with the smaller CCM dataset for controlling for size and book-to-market ratio.

		Number of Stocks				Returns (%)									Capitalization ($,000)		
	Industry	Mean	Min	Median	Max	Mean	Std. Dev.	Skewness	Kurtosis	Min	P(0.25)	Median	P(0.75)	Max	Mean	Median	N. Obs.
1	Candy and Soda	17	9	16	30	1.35	11.1	1.29	9	-69.96	-4.17	0.56	5.78	102	7531	145	9888
2	Tobacco Products	9	4	9	15	1.35	13.4	4.20	62	-85.62	-3.96	0.75	5.65	263	5898	310	5418
3	Telecommunications	136	20	139	236	1.15	22.4	6.26	148	-93.97	-7.51	0.00	7.75	867	3175	224	64301
4	Pharmaceutical Products	224	28	249	316	1.49	23.1	5.20	154	-97.22	-9.52	-0.00	9.08	1350	2935	131	98070
5	Aircraft	28	19	28	39	1.38	14.8	2.72	36	-85.19	-6.25	0.00	7.46	348	2533	107	17510
6	Insurance	152	8	155	209	1.18	12.7	1.71	22	-95.00	-4.43	0.32	6.06	257	2376	179	78253
7	Petroleum and Natural Gas	228	92	234	402	0.95	19.9	9.82	558	-98.13	-8.20	0.00	7.77	1577	2259	70	124967
8	Computers	169	20	193	266	1.15	22.1	3.44	46	-96.00	-9.76	-0.00	9.23	700	2195	67	82682
9	Consumer Goods	111	40	116	164	1.11	15.7	7.41	399	-91.67	-6.22	0.00	7.02	1100	1938	53	63443
10	Defense	9	4	9	12	1.48	14.9	1.55	12	-80.88	-6.06	0.38	7.48	171	1895	164	5203
11	Utilities	182	107	195	240	1.02	10.0	5.00	146	-88.89	-2.92	0.72	4.55	500	1628	360	109596
12	Chemicals	88	64	90	114	1.21	14.8	2.72	37	-91.67	-5.88	0.00	7.02	402	1574	129	55107
13	Retail	260	125	266	377	1.03	17.0	4.63	133	-94.85	-6.73	0.00	7.53	937	1508	75	154077
14	Banking	498	34	484	879	0.99	12.8	3.56	79	-97.83	-3.91	0.40	5.28	540	1321	70	217635
15	Autos	72	47	71	110	0.99	14.5	1.67	19	-88.04	-6.34	0.00	7.13	270	1311	123	44753
16	Business Supplies	49	22	51	70	1.13	13.2	3.63	82	-95.91	-5.06	0.28	6.57	414	1284	229	29496
17	Electronic Equipment	241	64	255	339	1.39	20.5	4.02	94	-96.04	-9.04	-0.00	9.09	1034	1263	56	137962
18	Business Services	602	25	550	1127	1.21	23.3	4.73	103	-97.65	-9.40	-0.00	8.91	1267	1207	79	266125
19	Shipbuilding, Railroad Eq.	10	5	9	14	1.16	14.0	1.75	20	-63.16	-5.75	0.00	7.02	226	1169	131	5844
20	Electrical Equipment	126	38	141	227	1.32	21.8	5.77	182	-95.00	-8.77	-0.00	8.43	1180	1139	46	60114
21	Food Products	83	44	84	124	1.21	13.6	2.65	35	-82.29	-5.17	0.00	6.25	329	1138	80	51064
22	Alcoholic Beverages	19	10	18	28	0.93	13.1	2.08	25	-93.44	-5.17	0.00	6.12	250	1117	87	11291
23	Entertainment	72	22	65	124	0.97	22.7	7.55	241	-92.86	-8.96	-0.00	8.11	1020	1064	38	37051
24	Printing and Publishing	55	17	59	76	1.20	15.6	5.05	114	-94.74	-5.51	0.00	6.67	600	1031	129	31470
25	Medical Equipment	150	9	155	235	1.23	22.6	19.70	1854	-95.27	-8.97	-0.00	8.57	2400	1011	60	70183
26	Transportation	110	66	106	160	1.09	15.9	3.38	62	-94.37	-6.43	0.00	7.32	518	1000	93	67633
27	Trading	474	45	580	714	1.31	13.4	3.97	83	-99.19	-4.17	0.33	5.88	641	965	70	202047
28	Machinery	167	87	181	233	1.27	15.9	3.67	76	-95.27	-6.52	0.00	7.48	589	958	63	100959
29	Restaurant, Hotel, Motel	114	21	113	201	0.84	16.9	3.71	80	-90.32	-7.14	0.00	7.27	701	898	55	58640
30	Shipping Containers	36	8	38	60	1.34	14.2	5.67	158	-72.73	-5.26	0.00	6.60	556	874	89	18449
31	Miscellaneous	252	4	248	557	0.84	22.7	17.98	1022	-92.88	-7.96	-0.00	7.31	1598	845	174	29596
32	Coal	10	4	10	15	1.08	17.3	3.80	69	-83.19	-6.95	0.00	7.85	417	803	142	5696
33	Steel Works, Etc.	80	36	87	108	1.08	16.8	31.61	3405	-95.00	-6.38	0.00	7.09	1900	694	92	48159
34	Healthcare	119	1	120	190	1.25	20.8	4.32	115	-92.31	-8.82	0.00	9.09	950	688	65	48697
35	Precious Metals	29	6	31	54	0.94	23.0	3.89	52	-90.98	-10.61	-0.00	8.70	567	667	33	13480
36	Nonmetallic Mining	29	10	30	41	1.06	20.1	7.66	266	-88.04	-8.38	-0.00	7.81	918	665	66	17449
37	Measuring and Control Equip.	97	21	107	148	1.46	21.0	16.12	1065	-96.23	-8.00	-0.00	8.18	1700	603	42	52686
38	Wholesale	214	42	200	364	1.05	19.4	5.24	127	-95.45	-7.69	0.00	7.69	875	505	41	110311
39	Personal Services	51	7	49	83	0.88	20.3	8.61	355	-93.90	-7.80	0.00	7.69	1100	434	50	26942
40	Apparel	74	23	75	125	0.86	15.7	2.36	37	-95.00	-6.91	0.00	7.11	454	432	29	43280
41	Construction	58	17	59	82	0.96	18.7	4.64	95	-93.21	-8.00	-0.00	7.88	667	429	50	32976
42	Construction Materials	152	38	142	234	1.27	15.3	3.58	66	-92.08	-6.09	0.00	6.96	540	424	38	81710
43	Recreational Products	50	20	50	79	0.73	19.0	3.75	57	-90.83	-8.62	-0.00	7.69	500	311	26	29373
44	Rubber and Plastic Products	45	12	47	72	1.26	16.9	1.97	17	-95.83	-7.11	0.00	7.48	240	296	27	24039
45	Fabpricated Products	21	6	23	32	1.11	15.9	4.05	71	-78.87	-6.50	0.00	7.18	400	228	40	11102
46	Agriculture	19	3	19	33	0.70	18.3	3.36	40	-88.89	-7.22	-0.00	6.67	317	202	49	9424
47	Real Estate	52	20	56	100	0.65	18.8	4.61	81	-82.07	-7.69	-0.00	6.65	577	186	22	29108
48	Textiles	55	9	53	100	0.95	15.2	2.01	22	-89.49	-6.51	0.00	6.91	348	148	31	27579
49	Unclassified	42	9	41	80	0.98	19.5	2.56	21	-97.37	-8.25	-0.00	7.59	284	146	30	18892
50	Market	5110	1963	5034	7517	1.33	4.5	-0.48	2	-22.13	-1.45	1.66	4.30	18	136164258	75495133	2939730

Table 1: Stock-wise summary statistics for the 07:1962–12:2015 monthly dataset. Sorted on the mean stock Capitalization. For each industry and each month, I calculate the number of stocks, the monthly return for each stock and the average monthly capitalization of each stock. The statistics correspond to each industry for the selected variable (number of stocks, monthly average return per stock, monthly average capitalization per stock). The "N. Obs" column presents the monthly observations for each industry during the whole sample. The last row presents the market-wide monthly statistics.

6 Empirical Results

I begin the Empirical Results section by presenting figures of the calculated average industry volatility series for both weighting schemes. I denote the value- and equally-weighting scheme with the subscripts *vw* and *ew*, respectively. In order to provide an overview of the aggregate variables used in the main part of the thesis, I continue with tables of descriptive statistics. Next, I present the results of the hypotheses testing as described in Section 4.1.2.

6.1 Figures and Descriptive Statistics

Figures 1 and 2 present the calculated average industry-level volatility IND with a value- and equal-weighting scheme, respectively. For comparison purposes with Campbell et al., I plot the raw monthly volatility time series in the Panels A. In Panels B, the figures plot the lagged moving average of twelve months, which I denote with MA(12), and I visually confirm a slow moving component as in Campbell et al..

Campbell et al. (2001) thoroughly describe the calculated volatility series until the end of 1997. After the publication of Campbell et al., there are two periods of elevated average industry volatility; during 1998–2004 and 2008–2010. During these periods there was the Russian financial crisis in 1998 with the devaluation of the ruble, the dot-com bubble in 2000, the September 11 attacks in 2001, the general stock market downturn of 2002 and the financial crisis that had obvious impacts in volatility during 2008–2010 and a small raise in volatility because of the August 2011 plummeting.

Table 2 presents basic descriptive statistics for the aggregate volatility series at the market-, industry-, and firm-level, which I denote with MKT, IND and $FIRM$, respectively, as defined above. For the volatility series, I present basic statistics for the two weighting schemes, which I denote with the subscript *vw* and *ew* for the value- and equally-weighting scheme, respectively. There are two main differences with Campbell et al.. First, after the publication of their paper, the volatilities increased to unprecedented levels. Additionally, in an untabulated investigation, I find that although Campbell et al. stress the increasing number of stocks from 1962 to 1997 when the paper's dataset ends, after 1997, there is a gradual decrease in the number of stocks and in 2015 the number of stocks is similar to the number of stocks during the '70s. Second, Table 2 shows that the increasing linear trend of the value-weighted average stock idiosyncratic volatility, $FIRM$,

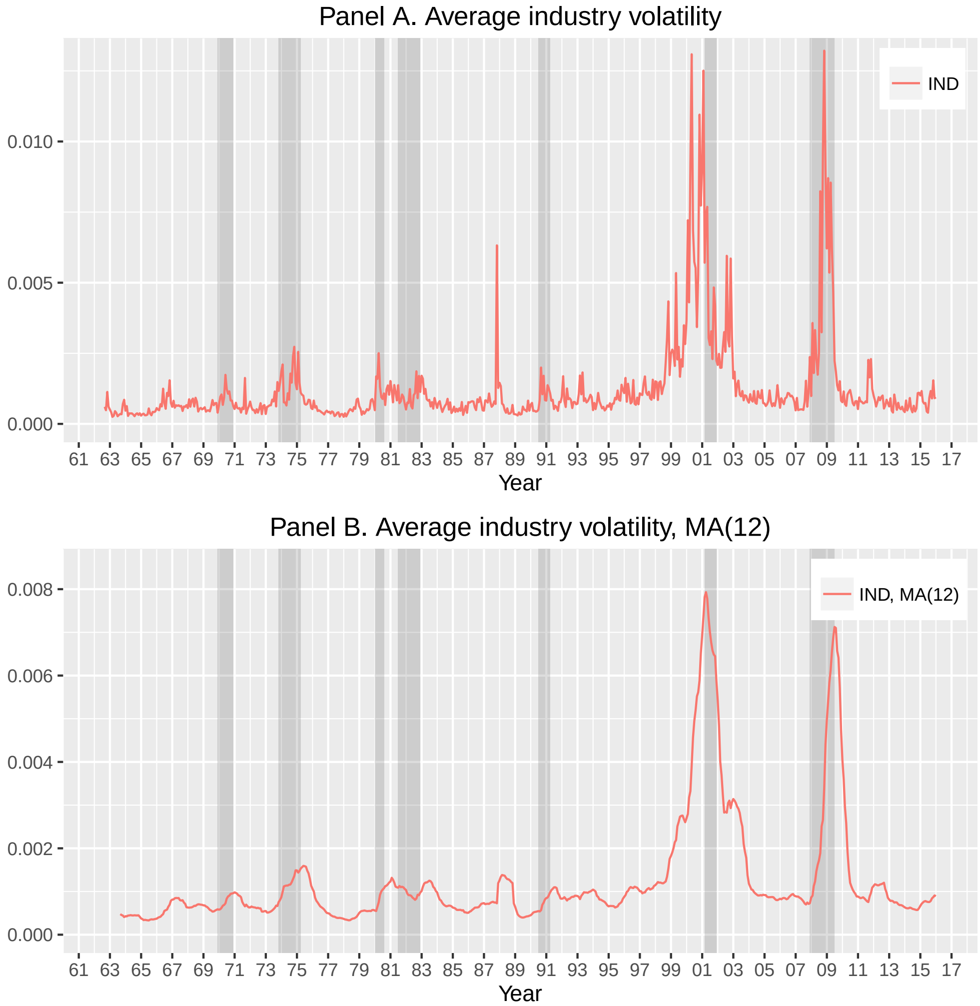

Figure 1: Average value-weighted industry volatility, $INDvw$. Panel A plots the raw average industry volatility series as calculated from equation (4.8) implementing the value-weighting scheme. $INDvw$ is calculated based on normal and not in percentage returns, so as the figure to be comparable with the figure of Campbell et al. (2001). Panel B plots a twelve-month moving average (MA(12)) of $INDvw$. NBER recession periods are shaded in grey in both panels.

which I denote with $FIRMvw$, changes direction. The coefficient of the linear trend takes the positive magnitude of 8.619×10^6 during 07:1962–12:1997 and becomes -5.62×10^7 during 01:1998–12:2015. Hence, at the firm level, the increasing aggregate idiosyncratic stock volatility which is documented in Campbell et al. seems to be reversed after the publication of their paper. This result is also confirmed by Brandt et al. (2014, p. 873) who identify a structural breakpoint in April 2000. Brandt et al. propose a behavioural

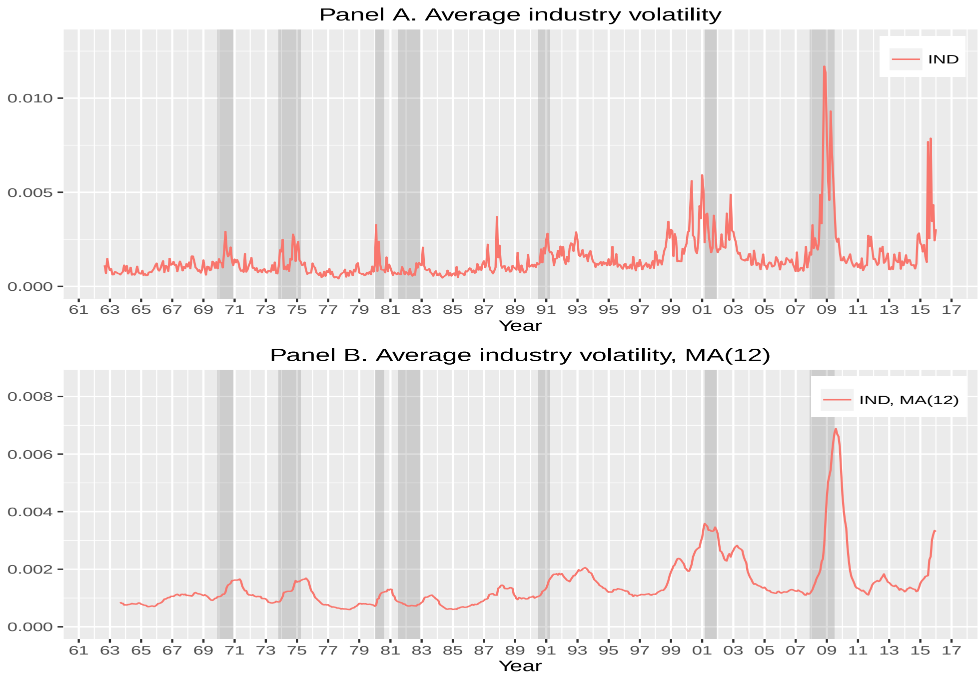

Figure 2: Average value-weighted industry volatility, $INDew$. Panel A plots the raw average industry volatility series as calculated from equation (4.8) implementing the value-weighting scheme. $INDew$ is calculated based on normal and not in percentage returns, so as the figure to be comparable with the Figure 1. Panel B plots a twelve-month moving average of (MA(12)) $INDew$. NBER recession periods are shaded in grey in both panels.

explanation for this change in the trend, based on retail trading. They find that low-priced stocks are associated with higher idiosyncratic volatility and they conjecture that the episodically higher idiosyncratic stock volatility was, at least partially, induced by retail investors, who prefer low-priced stocks. In contrast, Lesmond, Pan and Zhao (2016) explain the trend reversal from a microstructure perspective and argue that the trend is reversed in early 2001 because of the decimilsation in stock quotes.

The same change in the trend direction appears to be the case for $INDvw$ which also appears to have a negative trend during 01:1998–12:2015 with a significant t-statistic of -5.96. Although in the two subperiods there seem to be conflicting linear trends in the volatility series, along the whole period of 07:1962–12:2015 there seems to be an upward linear trend. However, this finding should be perceived with caution because it is not based on comprehensive trend analysis, like of Bekaert, Hodrick and Zhang (2012) who do not document an upward trend in the idiosyncratic volatility. During the two subperiods of 07:1962–12:1997 and 01:1998-12:2015 the volatility series experience a reverse in their linear trend from positive to negative, with the exception of the equally-weighted $MKTew$, which does experience a reverse in the trend, but from the negative magnitude of -1.15×10^{-3} to the positive magnitude of 5.25×10^{-3}.

With respect to the absolute level of the means of the series, average industry volatility, IND, continues to be lower than the aggregate market-wide volatility, MKT, and the average stock idiosyncratic volatility, $FIRM$, during 01:1998–12:2015. However, the relative level of the mean of the value-weighted average industry volatility, $INDvw$, compared to $FIRMvw$ appears to have been increased twofold; the ratio of $INDvw$ to $FIRMvw$ is approximately 0.14 during 07:1962–12:1997 and 0.28 during 01:1998-12:2015. Hence, in relation to average firm volatility, the average industry volatility seems to be increased during the last 18 years. This finding supports the claim of the thesis, that industry volatility, could be a priced factor for the stock returns, since stocks with higher idiosyncratic industry volatility should demand a premium. With respect to the equally-weighted scheme, the relative level of $INDew$ to $FIRMew$ is also increased, with a ratio of approximately 0.5 to 0.58.

Considering the market volatility, the value-weighted average industry volatility, $INDvw$ with respect to the value-weighted market volatility, $MKTvw$, remains around the same levels, but the equally-weighted $INDew$ is decreased relative to $MKTew$. Specifically, the relative level of $INDvw$ compared to $MKTvw$ appears to have been increased by around 12%, from 0.55 during 07:1962–12:1997 to 0.62 during 01:1998-12:2015. However, in the case of the equally-weighted scheme, $INDew$ is decreased relative to $MKTew$ from the first subperiod to the second. The ratio of the means of $INDew$ to $MKTew$ is approximately 1.08 during 07:1962–12:1997 and 0.74 during 01:1998-12:2015.

Moreover, the standard deviation of volatility has increased for all the volatility series and especially at the industry level, experiences the largest increase, of more than 5 times for $INDvw$ and more than 3 times for $INDew$. For example, the standard deviation of $INDvw$ is 0.48×10^{-3} during 07:1962–12:1997 and 2.15×10^{-3} during 01:1998-12:2015, experiencing an increase of 512.5% while the standard deviation of $FIRMvw$ increased from 2.38×10^{-3} to 6.98×10^{-3} during the respective periods, experiencing only an increase of 293.3%. The increase in the standard deviations is easy to comprehend, because of the financial crisis during the second subperiod. As Schwert (1989) concludes, aggregate economic series seem to be more volatile during recession periods. Moreover, he related this result with the existence of "operating leverage", which in the case of firms with high fixed

Period	Series	Mean (10^3)	Std. Dev. (10^3)	Std. Dev. detrended (10^3)	Linear Trend (10^6)	t-statistic
07:1963–12:2015	MKTvw	2.11	4.24	4.15	4.61	5.06
	MKTew	1.67	3.42	3.34	4.06	5.54
	INDvw	1.25	1.63	1.56	2.55	7.47
	INDew	1.47	1.17	1.08	2.58	10.93
	FIRMvw	6.45	4.61	4.54	4.25	4.27
	FIRMew	33.59	24.70	23.48	42.23	8.20
07:1963–12:1997	MKTvw	1.41	3.02	3.02	1.42	1.15
	MKTew	1.01	2.12	2.12	-1.15	-1.31
	INDvw	0.78	0.48	0.47	0.79	4.09
	INDew	1.09	0.48	0.47	0.96	4.98
	FIRMvw	5.78	2.38	2.16	8.41	9.46
	FIRMew	31.25	20.43	13.35	129.25	23.51
01:1998–12:2015	MKTvw	3.46	5.67	5.67	-4.97	-0.80
	MKTew	2.95	4.81	4.79	5.25	1.00
	INDvw	2.15	2.46	2.28	-14.86	-5.96
	INDew	2.19	1.67	1.67	-1.04	-0.57
	FIRMvw	7.72	6.98	6.02	-56.61	-8.60
	FIRMew	38.08	30.87	27.46	-225.71	-7.52

Table 2: Descriptive statistics for the aggregate volatility series. The volatility series are calculated based on normal and not in percentage returns, so as to be comparable with Campbell et al. (2001)

costs, reflects the faster fall in the net profits relative to the revenues, when demand falls because of the recession. Especially for the average industry volatility, which experiences the largest increase, a possible explanation could be that the uncertainty which influences the industries is increased during the recent years. At an aggregate level, investors seem to react more intensely to news affecting whole industries, compared to news which affect specific stocks or the market as a whole. This finding supports the rejection of hypothesis 1, as explained in Section 3.1.

I present the variable descriptive statistics of the cross-sectional sample in Table 3, which I describe in the previous Section 4.1.3. The mean monthly return of the cross-sectional sample, during 07:1963–12:2015, is 0.37%, while the mean excess return (XRET) over the one-month T-bill rate as obtained from the Kenneth French's data library is -0.04%. The natural logarithms of size (market equity) and book-to-market ratio are in accordance with the literature, as in Fu (2009).[9] The factor loadings (betas or sensitivities) of the volatility series and the CAPM, FF3-5 factors indicate how sensitive the stock prices

[9] My table concerns the cross-sectional sample. In untabulated results, I closely replicate the return variables of Table 3 of Fu (2009), using a pooled sample.

are with respect to the corresponding risk factor.[10] In general, the factor sensitivities of the volatility series particularly with respect to the mean, standard deviation and interquartile range (column I.Q.R. of the table) have substantially different characteristics than the other factor loadings. Their standard deviation is much lower, in general, than the rest of the factors and their mean is very close to zero. The factor sensitivity (or loading or beta) signifies the relative movement of the stock price with respect to the particular factor. For example, a 1.15 beta means that the stock return will increase by 1.15% if there is a 1% increase in the corresponding factor. Table 3, line 9, shows for the beta of the excess market return ($MktRF$) that half of the stocks have a dispersion (I.Q.R.) of 0.91, ranging from 0.64 to 1.54. Thus, the reaction of the stocks to changes in the excess market return, are not as much concentrated across all stocks, compared to the beta of the value-weighted average industry volatility (β_{INDvw}, line 14). With respect to β_{INDvw}, fifty percent of the stocks have only a dispersion of 0.36, ranging from -0.29 to 0.07. Thus, the stocks, relative to the excess market return, react more weakly to the changes in average industry volatility.

Moreover, the stocks' betas of industry volatility measures are more dispersed than the betas of market-wide or idiosyncratic stock-related volatility measures. This indicates that the returns of the stocks react in a broader way to changes in the respective industry volatility factors, compared to market-wide or stock idiosyncratic related volatility measures. However, this reaction is much lower than the reaction of the stock returns to the factor changes of the baseline models. In the case of the RMW, the risk factor that corresponds to operating profitability, half of the stocks' returns react by 533% more compared to the risk of the value-weighted average industry volatility, $INDvw$, since the interquartile range is 1.92 for the former and 0.36 for the latter.

Concluding, the volatility series at the aggregate level, have reversed their positive trend and literature indicates that this reversal occurred in the early 2000s. The average industry level remains at lower levels compared to market-wide and the aggregate average stock idiosyncratic volatility. Nonetheless, its relative level with respect to the average stock idiosyncratic volatility has increased, giving support to the alternative of the first hypothesis, which I examine in the next section.

[10] In untabulated results, I experiment with bivariate models, as in $XRET_t = \alpha + \beta_{MktRF} MktRF_t + \beta_{INDvw} INDvw_t + \varepsilon_t$, with two subperiods, 01:1991–12:2015 and 01:1998-12:2015 does not change the picture.

#	Variable	Mean	Std. Dev.	Skewness	Kurtosis	Min	P(0.25)	Median	P(0.75)	Max	I. Q. R.	N. Stocks	N. Obs.
1	$\bar{\hat{RET}}$	0.37	4.16	-1.19	23.45	-61.91	-0.38	1.18	2.04	79.52	2.42	23496	2894467
2	$\bar{\hat{X}RET}$	-0.04	4.17	-1.19	23.38	-62.33	-0.80	0.77	1.65	79.45	2.45	23496	2894467
3	$\bar{I}IN\hat{D}vw$	14.48	14.22	3.68	22.35	0.69	6.11	10.43	17.71	210.23	11.60	23496	2894467
4	$\bar{I}IN\hat{D}ew$	7.01	8.67	7.71	136.35	0.27	2.56	4.91	8.36	315.22	5.80	23496	2894467
5	$\bar{A}IFI\hat{R}Mvw$	100.15	61.51	2.19	7.73	6.63	60.71	83.66	123.39	688.60	62.68	23496	2894467
6	$\bar{A}IFI\hat{R}Mew$	446.08	260.75	1.11	1.54	20.40	248.75	382.86	603.95	2556.20	355.21	23496	2894467
7	$\bar{I}FI\hat{R}Mvw$	635.49	1562.37	41.66	3329.22	0.59	146.59	317.75	707.95	145719.72	561.36	23496	2894467
8	$\bar{I}FI\hat{R}Mew$	612.91	1537.91	41.78	3330.39	0.41	135.63	299.99	678.34	143363.91	542.71	23496	2894467
9	$\bar{\hat{\beta}}_{MktRF}$	1.11	0.83	0.68	6.23	-9.11	0.64	1.08	1.54	8.03	0.91	19752	2307531
10	$\bar{\hat{\beta}}_{SMB}$	1.33	1.23	1.06	11.38	-10.10	0.68	1.30	2.05	21.62	1.37	19752	2307531
11	$\bar{\hat{\beta}}_{HML}$	-0.44	1.41	-0.56	6.71	-15.57	-1.26	-0.40	0.17	14.98	1.43	19752	2307531
12	$\bar{\hat{\beta}}_{RMW}$	-0.88	2.07	-1.01	10.18	-30.64	-1.94	-0.75	-0.02	16.26	1.92	19752	2307531
13	$\bar{\hat{\beta}}_{CMA}$	-0.82	1.83	-0.79	10.74	-27.82	-1.79	-0.82	-0.07	16.28	1.73	19752	2307531
14	$\bar{\hat{\beta}}_{INDvw}$	-0.07	0.74	4.00	143.77	-9.44	-0.29	-0.09	0.07	28.83	0.36	19752	2307531
15	$\bar{\hat{\beta}}_{IINDvw}$	-0.07	0.68	3.72	135.50	-9.22	-0.25	-0.07	0.06	21.16	0.31	19752	2307531
16	$\bar{\hat{\beta}}_{MKTvw}$	-0.10	0.29	0.24	53.80	-4.35	-0.18	-0.09	-0.03	7.52	0.15	19752	2307531
17	$\bar{\hat{\beta}}_{FIRMvw}$	-0.03	0.18	2.22	85.93	-2.87	-0.09	-0.03	0.01	6.10	0.10	19752	2307531
18	$\bar{\hat{\beta}}_{AIFIRMvw}$	-0.02	0.12	0.30	40.80	-2.06	-0.05	-0.02	0.01	2.61	0.07	19752	2307531
19	$\bar{\hat{\beta}}_{INDew}$	0.03	0.78	2.67	40.18	-8.15	-0.20	-0.01	0.21	16.24	0.41	19752	2307531
20	$\bar{\hat{\beta}}_{IINDew}$	0.03	1.99	1.01	38.13	-28.06	-0.47	-0.04	0.35	35.16	0.82	19752	2307531
21	$\bar{\hat{\beta}}_{MKTew}$	-0.11	0.36	5.57	226.32	-3.60	-0.21	-0.11	-0.03	15.91	0.18	19752	2307531
22	$\bar{\hat{\beta}}_{FIRMew}$	0.01	0.04	2.47	30.20	-0.48	-0.01	0.01	0.02	0.87	0.03	19752	2307531
23	$\bar{\hat{\beta}}_{AIFIRMew}$	0.01	0.03	5.39	114.72	-0.39	-0.00	0.00	0.01	1.07	0.02	19752	2307531
24	$\bar{\hat{\ln}}ME$	4.27	1.96	0.31	-0.12	-1.51	2.82	4.16	5.59	12.80	2.77	17845	2076995
25	$\bar{\hat{\ln}}BM$	-0.72	0.88	-0.83	2.34	-8.79	-1.22	-0.62	-0.12	2.42	1.10	17845	2076995

Table 3: Variable descriptive statistics. I average first by stock and then calculate the descriptive statistics. For each stock, I assign an average value of the corresponding variable (rows of the table). The table reports the summary statistics of these average values across all stocks. RET and $XRET$ are the monthly raw and excess returns in percentage. The volatility variables are calculated based on the percentage return for comparison purposes with the Fama and French factors, which concern portfolios' returns in percentage. For each volatility variable and stock, I run time-series regressions with a rolling window of 60-months, $XRET_t = \alpha + \beta_{Variable} Variable_t$ and I average the estimated β for each stock. The reported $\bar{\hat{\beta}}_{Variable}$ are the averaged estimated β across all stocks. The $\ln BM$ and $\ln ME$ are the natural logarithms of the Book-to-Market and Market Equity variables used in the cross-sectional regressional analyses as controls calculated with data from the Compustat/CRSP merged database. I calculate ME based on data available in June and for the Book-to-Market I calculate the book value with data of the fiscal year end. Following Fama and French (1993), I calculate $\ln BM$ with data available in the calendar year y which are assumed to be known to the stock from the end of June of year $y+1$ untill the end of May of year $y+2$. The period of the sample is from July 1963 to December 2015.

6.2 The pricing of the average idiosyncratic industry volatility as factor

I begin the empirical investigation of the pricing of industry volatility, by analysing the relationship between the betas of the three aggregate volatility measures, at the market-, industry- and firm-level, to the excess returns, in order to test hypothesis 1 of Section 3.1. To keep the analysis simple and emphasize actual investment returns, I concentrate on the value-weighting scheme. I present complete tables for every tested specification for both the value- and equally-weighting schemes in the web appendix.

Table 4 presents the results of the second step of the Fama-MacBeth regression analysis. I present the risk premia of each beta, that is, the average coefficients of the betas of the cross-sectional regressions during 07:1968–12:2015. As I describe in Section 4.1, for each risk premium, I also calculate the Newey-West (1987) t-statistics with a lag of 5 months, as well as the simple and adjusted coefficients of determination, R^2, and R^2-adj in parentheses, respectively. On Panel A, I augment the betas of the factors of the three baseline (CAPM, FF3, and FF5) models with the betas for the three aggregate volatility series for the value-weighting scheme: (i) the market-wide volatility, $MKTvw$, (ii) the average idiosyncratic industry volatility, $INDvw$, and (iii) the aggregate average idiosyncratic firm volatility, $FIRMvw$. First, I estimate the baseline models in specifications 1, 4 and 7. Then, I augment the baseline modles with the variable of interest, which is for testing hypothesis 1 the beta of $INDvw$, specifications 2, 5 and 8. Third, I augment the previous specifications with the other volatility series as controls, in specifications 3, 6 and 9. To preserve space, I present additional specifications in the web appendix. Panel B of Table 4 additionally controls for the magnitudes of size and value, as characteristics. Specifications 1, 3 and 5 of Panel B augment the baseline models with the variable of interest (here β_{INDvw}) and the magnitudes of size ($\ln ME$) and value ($\ln ME$). Next, specification 2, 4 and 6 augment the previous specifications with the other volatility series as controls. For Panel A, I use the CRSP database exclusively, while for Panel B, the Compustat/CRSP merged (CCM) database, in order to calculate the size and value controls.

In the specifications 1, 4 and 7, of Panel A of Table 4, I find a negative and not significant risk premium of the beta of the excess market return, β_{MktRF}, which ranges from -0.104 for the baseline CAPM model to -0.068 for the FF5 model. This result is consistent with the recent literature which examines individual stocks as basis assets, as in Jegadeesh, Noh, Pukthuanthong, Roll and Wang (2016, Table 5). In specifications 1, 3 and 5 of Panel B, where I also control for the magnitudes of size and value, the risk premium of β_{MktRF} becomes positive and the change in its sign occurs because of the different sample of Panel B. This positive sign is confirmed in Chordia, Goyal and Shanken (2015, Table 3), who also use size and value controls. Chordia et al. (2015) also find similar risk premia for the rest of the FF3 and FF5 factors, all of them statistically not significant, when they control for size and value. In Panel A of Table 4, the risk premia of β_{HML} (the value factor) are statistically significant at the 5% significance level for every specification, however they are not significant in Panel B, when I control for value and size with the logarithms of the book-to-market ratio and market equity, respectively.

In Panel A of Table 4, specifications 2, 5 and 8, I find that the risk premium of β_{INDvw} is only marginally significant at the 10% significance level and it ranges from -0.876 for the FF3 augmented model to -0.966 for the CAPM augmented model. In Panel A, specification 2, the risk premium of $INDvw$ is -0.966 for the CAPM augmented model, while in Panel B, specification 1, it is -0.88 after controlling for size and value. Approximately half of the difference in the β_{INDvw} coefficients between the two panels is due to the different sample since not every stock of Panel A has data in the CRSP/Compustat Merged (CCM) database of Panel B. In the web appendix, where I separately control for size and value, I show that the other half of the difference in the risk premia of β_{INDvw} is due to the size control. Hence, this difference might indicate that part of the association of the volatility factor sensitivities with the stock returns is explained by size and hence size acts as a *confounder variable*. In other words, the association of β_{INDvw} with stock returns is smaller when I control for size only, while it is larger when I do not and I only augment the baseline models with β_{INDvw}. Moreover, in Panel B, where I control for size and value, the coefficients on the magnitudes of size ($\ln ME$) and value ($\ln BM$) are consistent with the literature. For example, Lewellen (2011, Table 2) finds a positive and negative statistically significant coefficients for value and size magnitudes respectively.[11] I also observe a confounding relation between the risk premium of β_{HML} and the logarithm of the book-to-market ratio, $\ln BM$, since comparing specifications 6 of Panel A and 4 of Panel B, the risk premium of β_{HML} drops from the significant at the 5% significance level 0.144 to 0.07 (not statistically significant). I find support for this relation in the extensive tables of the web appendix where I separately control for the magnitudes of size and value.

Considering the descriptive statistics of Table 3, line 14 for $\bar{\beta}_{INDvw}$, one standard deviation of β_{INDvw} is 0.74. Hence, given the specification 3 of Table 4 for the CAPM

[11] Additionally, they are also consistent with the studies of Chordia, Goyal and Shanken (2015, Table 3), Bali, Cakici and Whitelaw (2011, Table 7), Lin, Palazzo and Fang (2016, Table 15), Avramov and Chordia (2006, Table 4), Jegadeesh, Noh, Pukthuanthong, Roll and Wang (2016, Table 5).

augmented model, and the risk premium of β_{INDvw}, which is -0.887, one standard deviation of β_{INDvw} is associated with lower excess returns by approximately -0.656% in a monthly basis. This associated change is economically important and supersedes the changes of the risk premia of the betas of variables of the baseline models CAPM, FF3 and FF5. The risk premia of the betas of $MKTvw$ and $FIRMvw$ are statistically significant at 5%, except for specification 4 and 6 of Panel B where they are significant at 10%. Their magnitudes are four and three times larger than the risk premia of β_{INDvw}, respectively (specifications 3, 6 and 9). One standard deviation of β_{MKTvw} is associated with approximately -0.95% change in the excess returns, yielding a risk premium with higher economic importance than of the risk premium of β_{INDvw}. Next, one standard deviation of β_{FIRMvw} is associated with approximately -0.51% change in the excess returns, yielding a risk premium with lower economic importance than of the β_{INDvw}. These findings are consistent with the strand of literature which find a negative relation between the stock returns and market-wide volatility (e.g. Glosten, Jagannathan and Runkle (1983)) and the aggregate idiosyncratic stock volatility (e.g. Guo and Savickas (2008)).

However, in Panel B of of Table 4 and more extensively in the web appendix, the risk premium of β_{INDvw} does not survive the control of β_{MKTvw} in addition to the size control, $\ln ME$, for every tested specification (2, 4 and 6).Thus, the relation of the β_{INDvw} to the stock returns seems to be explained by a linear combination of β_{MKTvw} and $\ln ME$, since it becomes statistically weak when I include the latter two variables. Hence, the table indicates that hypothesis 1, which postulates that average industry volatility is not priced, is not rejected at the 10% significance level. Moreover, the relation of the betas of the market volatility and the aggregate average firm volatility seems consistent with the strand of the literature which finds a negative relation between volatility and stock returns.

Panel A

#	$\hat{\lambda}_{\text{intercept}}$	$\hat{\lambda}_{\beta_{MktRF}}$	$\hat{\lambda}_{\beta_{SMB}}$	$\hat{\lambda}_{\beta_{HML}}$	$\hat{\lambda}_{\beta_{RMW}}$	$\hat{\lambda}_{\beta_{CMA}}$	$\hat{\lambda}_{\beta_{INDvw}}$	$\hat{\lambda}_{\beta_{MKTvw}}$	$\hat{\lambda}_{\beta_{FIRMvw}}$	R^2, $\bar{R}^2$ (in %)
1	0.896	-0.104								1.595
	(4.48)***	(-0.817)								(1.569)
2	0.853	-0.073					-0.966			1.896
	(4.197)***	(-0.558)					(1.733)*			(1.842)
3	0.837	-0.1					-0.887	-3.271	-2.813	2.427
	(4.225)***	(-0.814)					(1.742)*	(2.046)**	(2.103)**	(2.321)
4	0.827	-0.083	-0.014	0.147						2.753
	(4.3)***	(-0.762)	(-0.194)	(2.34)**						(2.674)
5	0.789	-0.042	-0.007	0.142			-0.876			2.965
	(4.068)***	(-0.372)	(-0.102)	(2.248)**			(1.66)*			(2.86)
6	0.793	-0.061	-0.004	0.144			-0.826	-3.197	-2.65	3.273
	(4.109)***	(-0.571)	(-0.057)	(2.356)**			(1.713)*	(2.123)**	(2.085)**	(3.115)
7	0.811	-0.068	-0.012	0.142	-0.009	0.077				3.098
	(4.206)***	(-0.632)	(-0.166)	(2.318)**	(-0.188)	(1.802)*				(2.966)
8	0.778	-0.034	-0.003	0.142	-0.019	0.073	-0.909			3.277
	(4.004)***	(-0.3)	(-0.043)	(2.307)**	(-0.397)	(1.708)*	(1.669)*			(3.119)
9	0.785	-0.049	-0.005	0.14	-0.01	0.076	-0.837	-3.245	-2.706	3.537
	(4.049)***	(-0.46)	(-0.071)	(2.371)**	(-0.225)	(1.863)*	(1.668)*	(2.084)**	(2.064)**	(3.327)

Panel B

#	$\hat{\lambda}_{\text{intercept}}$	$\hat{\lambda}_{\beta_{MktRF}}$	$\hat{\lambda}_{\beta_{SMB}}$	$\hat{\lambda}_{\beta_{HML}}$	$\hat{\lambda}_{\beta_{RMW}}$	$\hat{\lambda}_{\beta_{CMA}}$	$\hat{\lambda}_{\beta_{INDvw}}$	$\hat{\lambda}_{\beta_{MKTvw}}$	$\hat{\lambda}_{\beta_{FIRMvw}}$	$\hat{\lambda}_{\text{ln.BM}}$	$\hat{\lambda}_{\text{ln.ME}}$	R^2, $\bar{R}^2$ (in %)
1	1.161	0.04					-0.88			0.274	-0.071	3.525
	(3.543)***	(0.337)					(1.745)*			(3.896)***	(1.691)*	(3.37)
2	1.176	0.01					-0.618	-2.237	-2.058	0.273	-0.068	3.912
	(3.652)***	(0.086)					(-1.58)	(2.043)**	(1.968)**	(3.865)***	(1.673)*	(3.681)
3	1.19	0.064	-0.021	0.072			-0.799			0.239	-0.081	4.16
	(3.966)***	(0.595)	(-0.362)	(1.331)			(1.709)*			(3.734)***	(2.233)**	(3.93)
4	1.201	0.032	-0.022	0.07			-0.668	-2.479	-2.168	0.246	-0.079	4.486
	(4.026)***	(0.31)	(-0.382)	(1.33)			(-1.583)	(1.924)*	(1.922)*	(3.842)***	(2.187)**	(4.181)
5	1.197	0.067	-0.019	0.066	0.014	0.019	-0.826			0.242	-0.082	4.497
	(3.97)***	(0.631)	(-0.346)	(1.26)	(0.335)	(0.477)	(1.729)*			(3.772)***	(2.269)**	(4.192)
6	1.217	0.039	-0.022	0.063	0.018	0.023	-0.716	-2.539	-2.26	0.248	-0.081	4.792
	(4.048)***	(0.378)	(-0.403)	(1.236)	(0.473)	(0.577)	(-1.559)	(1.845)*	(1.887)*	(3.865)***	(2.268)**	(4.411)

Table 4: ***Fama-MacBeth cross-sectional regression analysis (second step) for the value-weighted average industry volatility (INDvw) as risk factor.*** The left-hand side (test or basis assets) are excess returns of individual stocks. The right-hand side are betas of the CAPM-FF3-FF5 factors and the average industry volatility (IND) following Campbell et al. (2001). I use a value-weighting scheme (vw). In Panel A I control for the betas of market volatility ($\beta MKTvw$) and average firm volatility (β_{FIRMvw}), again with their respective weighting scheme, using exclusively the CRSP database. In Panel B I additionally control for size ($\ln BM$) and value ($\ln ME$), using the merged CRSP/Compustat (CCM) database. The period for the time-series 60-month rolling regressions to estimate the βs is 07:1963–12:2015. The period for the cross-sectional regressions is 08:1968–12:2015. Robust Newey-West (1987) t-statistics with 5 lags are reported in parentheses. *, **, *** denote significant coefficients for the 10%, 5% and 1% significance levels, respectively. The right-most column reports the average coefficient of determination, R^2 and $adj-R^2$ in parenthesis, across the cross-sectional regressions.

6.3 Idiosyncratic Industry volatility as industry-varying factor

In the previous section, I find that hypothesis 1 is not rejected at the 10% significance level because the risk premium of the beta of the average industry volatility is not statistically significant when I control for market-wide volatility in addition to the size control. Moreover, I indicate that market-wide volatiltiy and stock idiosyncratic volatility are negatively priced. In this section, I test hypothesis 2 which postulates that the idiosyncratic industry volatility, for the value-weighted weighting scheme, $IINDvw$, is not priced as an industry-varying factor. For example, in contrast to SMB, HML and $INDvw$ which I consider common risk factors among all the stocks, I treat $IINDvw$ as varying among stocks in different industries, as explained previously. As I explain in the previous section, I concentrate the analysis on the value-weighting scheme.

Table 5 presents the average risk premia of the cross-sectional regressions as calculated in the second step of the Fama-MacBeth procedure. The table has a similar form to the Table 4 of the previous section. In Panel A, I augment each of the CAPM-FF3-FF5 models with the beta of the idiosyncratic industry volatility, as discussed in the previous section, and I further control for the betas of market-wide volatility, β_{MKTvw}, and the betas of the average idiosyncratic firm volatility of each industry, $\beta_{AIFIRMvw}$, which I also treat as an industry-varying factor. In Panel B, I additionally control for the magnitudes of size and value. In both panels, the t-statistics are adjusted according to Newey-West (1987) with a lag of 5 months and I also include the simple and adjusted coefficients of determination in the right-most column.

Panel A of Table 5, indicates that the risk premia of the factors of the baseline models are consistent with the literature and Table 4 of the previous section. Panel A, specifications 2, 5 and 8, shows that compared to β_{INDvw} of Table 4, and augmenting the three baseline models only with β_{IINDvw}, the risk premia of β_{IINDvw} seem statistically stronger since they are significant at the 5% significance level. They range from -0.425 for the FF3 augmented model to -0.462 for the CAPM augmented model. However, after controlling for β_{MKTvw} and $\beta_{AIFIRMvw}$, I observe a drastic drop in the risk premia of β_{IINDvw}; in specifications 3, 6 and 9, the risk premia range from -0.151 for the FF3 augmented model to only -0.145 for the FF5 augmented model. This dramatic change signifies a strong confounding relationship of the β_{IINDvw} to the added betas of market

[12] In the web appendix, I separately control for β_{MKTvw} and $\beta_{AIFIRMvw}$ and I show that each of these betas have a strong confounding relationship to β_{INDvw}, which is slightly stronger for the case of $\beta_{AIFIRMvw}$.

wide volatility and the industry varying average idiosyncratic firm volatility.[12] Moreover, the risk premium of β_{IINDvw} is not statistically significant at the 10% significance level.

The economic importance of the risk premia of β_{IINDvw} is much lower than of β_{INDvw}, examined in Table 4. Considering the descriptive statistics of Table 3 one standard deviation of the betas of $IINDvw$ is 0.68. Hence, for the FF3 augmented model, specification 5 of Panel A, and the risk premium of β_{IINDvw} which is -0.425 a change of one deviation in β_{IINDvw} is associated with lower excess returns by approximately -0.29% in a monthly basis. Similarly, considering specification 6 and the standard deviation of $\beta_{AIFIRMvw}$ across all stocks, which is 0.12, a change of one standard deviation of $\beta_{AIFIRMvw}$ is associated with -0.08% lower stock returns in a monthly basis.

Panel B of Table 5 presents some even more surprising findings. First, the risk premium of the β_{MktRF} becomes negative; in specifications 2, 4 and 6, it takes the magnitutes of -0.022, -0.005 and -0.004 for the CAPM-FF3-FF5 augmented models, respectively. According to the Fama-MacBeth procedure, I average the risk premia of each month in the cross-sectional regressions in order to calculate the Fama-Macbeth estimator of the risk premia, also known as the mean group estimator. This change in the sign of β_{MktRF} occurs because the magnitudes of the risk premia of β_{MktRF} vary in the cross-sectional regressions around zero; they take negative and positive values, yielding a negative mean overall. Moreover, the t-statistic of the risk premium of β_{MktRF} is very close to zero and indicates that it is statistically indistinguishable from zero, this finding is not alerting.

Second, the risk premium of β_{IINDvw} becomes statistically significant at the 10% significance level. For example, in the CAPM augmented model the risk premium is estimated at -0.17 with a Newey-West t-statistic of 1.85. In the web appendix, I show that this occurs because of the different dataset used in Panel B, because I require stocks to have data in the CCM database. One potential explanation for this change in the statistical significance of the risk premium of β_{IINDvw} is that it could be a manifestation of the probable survivorship bias of the Compustat database, discussed in Kothari, Shanken, and Sloan (1995) and Barber and Lyon (1997). For example, Duffee (1995) for the 1977–1991 period reports that 48% of the firms with Compustat data are survivors, meaning that they have no more than 12 missing monthly observations, while of the firms without Compustat data only 17% are survivors. I find support for this explanation in the web appendix, where I show that requiring at least 48 months for a stock to be included in the regression dataset, renders the risk premium of β_{IINDvw} marginally statistically significant at the 10% significance level for the specifications 3, 6 and 9 of Panel A of Table 5.

Judging from the magnitudes of the coefficients and the fact that the risk premium of β_{INDvw} increases from -0.428 for the augmented CAPM model, specification 1 (Panel B), when I only control for size and value, to -0.17 in specification 2, losing approximately half of its absolute value, it is clear that there is a confounding relationship of β_{INDvw} and the controls. In the web appendix, I show that this occurs because of β_{MKTvw} and $\beta_{AIFIRMvw}$, while the size and value controls do not have a sufficient impact on the magnitude of the risk premium of β_{INDvw}. Hence, it is clear that some part of the strong significance of $\beta_{AIFIRMvw}$ is due to β_{IINDvw} and/or vice-versa. In other words, the idiosyncratic industry volatility and the average idiosyncratic firm volatility are not clearly separated. It could be the case, that the average firm idiosyncratic volatility within industry, captures an idiosyncratic industry volatility component or in the reverse order.

In conclusion, given that the risk premium of the beta of idiosyncratic industry volatility does not survive the controls of the beta of market-wide volatility and the average stock idiosyncratic volatility of each industry as an industry-varying risk factor, I conclude that I cannot reject hypothesis 2 at the 10% significance level. Moreover, I find a strong negative relation of the beta of the market-wide volatility to the stock returns and I confirm the strand of literature that also finds a negative relation, as in Glosten, Jagannathan and Runkle (1983).

Panel A

#	$\hat{\lambda}_{\text{intercept}}$	$\hat{\lambda}_{\beta_{MktRF}}$	$\hat{\lambda}_{\beta_{SMB}}$	$\hat{\lambda}_{\beta_{HML}}$	$\hat{\lambda}_{\beta_{RMW}}$	$\hat{\lambda}_{\beta_{CMA}}$	$\hat{\lambda}_{\beta_{IINDvw}}$	$\hat{\lambda}_{\beta_{MKTvw}}$	$\hat{\lambda}_{\beta_{AIFIRMvw}}$	R^2, $\bar{R}^2$ (in %)
1	0.896	-0.104								1.595
	(4.48)***	(-0.817)								(1.569)
2	0.882	-0.098					-0.462			1.699
	(4.388)***	(-0.8)					(2.164)**			(1.645)
3	0.906	-0.132					-0.147	-1.395	-0.64	1.994
	(4.485)***	(-1.215)					(-1.467)	(2.072)**	(-1.61)	(1.887)
4	0.827	-0.083	-0.014	0.147						2.753
	(4.3)***	(-0.762)	(-0.194)	(2.34)**						(2.674)
5	0.827	-0.075	-0.016	0.14			-0.425			2.817
	(4.281)***	(-0.73)	(-0.217)	(2.276)**			(2.137)**			(2.711)
6	0.856	-0.105	-0.025	0.129			-0.151	-1.472	-0.679	2.942
	(4.36)***	(-1.138)	(-0.348)	(2.154)**			(-1.489)	(2.215)**	(1.764)*	(2.784)
7	0.811	-0.068	-0.012	0.142	-0.009	0.077				3.098
	(4.206)***	(-0.632)	(-0.166)	(2.318)**	(-0.188)	(1.802)*				(2.966)
8	0.818	-0.068	-0.012	0.137	-0.013	0.077	-0.428			3.134
	(4.229)***	(-0.67)	(-0.168)	(2.297)**	(-0.293)	(1.831)*	(2.132)**			(2.976)
9	0.851	-0.101	-0.022	0.128	-0.005	0.081	-0.145	-1.484	-0.688	3.216
	(4.323)***	(-1.116)	(-0.311)	(2.242)**	(-0.129)	(2.032)**	(-1.434)	(2.199)**	(1.77)*	(3.005)

Panel B

#	$\hat{\lambda}_{\text{intercept}}$	$\hat{\lambda}_{\beta_{MktRF}}$	$\hat{\lambda}_{\beta_{SMB}}$	$\hat{\lambda}_{\beta_{HML}}$	$\hat{\lambda}_{\beta_{RMW}}$	$\hat{\lambda}_{\beta_{CMA}}$	$\hat{\lambda}_{\beta_{IINDvw}}$	$\hat{\lambda}_{\beta_{MKTvw}}$	$\hat{\lambda}_{\beta_{AIFIRMvw}}$	$\hat{\lambda}_{\text{ln.BM}}$	$\hat{\lambda}_{\text{ln.ME}}$	R^2, $\bar{R}^2$ (in %)
1	1.197	0.017					-0.428			0.26	-0.074	3.368
	(3.654)***	(0.154)					(2.217)**			(3.757)***	(1.755)*	(3.213)
2	1.232	-0.022					-0.17	-1.204	-0.789	0.255	-0.073	3.577
	(3.77)***	(-0.222)					(1.852)*	(2.234)**	(2.127)**	(3.686)***	(1.778)*	(3.345)
3	1.24	0.026	-0.036	0.075			-0.355			0.23	-0.083	4.023
	(4.119)***	(0.262)	(-0.617)	(1.458)			(2.074)**			(3.618)***	(2.271)**	(3.793)
4	1.251	-0.005	-0.04	0.069			-0.171	-1.28	-0.824	0.229	-0.08	4.155
	(4.141)***	(-0.055)	(-0.702)	(1.406)			(1.748)*	(2.205)**	(2.248)**	(3.605)***	(2.191)**	(3.849)
5	1.25	0.027	-0.036	0.068	0.017	0.029	-0.326			0.233	-0.084	4.368
	(4.128)***	(0.278)	(-0.656)	(1.353)	(0.443)	(0.738)	(1.934)*			(3.661)***	(2.301)**	(4.062)
6	1.263	-0.004	-0.037	0.061	0.017	0.033	-0.168	-1.33	-0.8	0.232	-0.081	4.451
	(4.151)***	(-0.047)	(-0.693)	(1.292)	(0.493)	(0.916)	(1.697)*	(2.11)**	(2.125)**	(3.66)***	(2.228)**	(4.069)

Table 5: ***Fama-MacBeth cross-sectional regression analysis (second step) for the value-weighted idiosyncratic industry volatility (IINDvw) as industry-varying risk factor.*** The left-hand side (test or basis assets) are excess returns of individual stocks. The right-hand side are betas of the CAPM-FF3-FF5 factors and the idiosyncratic industry volatility (IINDvw) following Campbell et al. (2001). I use a value-weighting scheme (vw). In Panel A I control for market volatility (MKT), and average idiosyncratic firm volatility (AIFIRM), again with their respective weighting scheme, using exclusively the CRSP database. In Panel B I additionally control for size ($\ln BM$) and value ($\ln ME$), using the merged CRSP/Compustat (CCM) database. The period for the time-series 60-month rolling regressions to estimate the βs is 07:1963–12:2015. The period for the cross-sectional regressions is 08:1968–12:2015. Robust Newey-West (1987) t-statistics with 5 lags are reported in parentheses. *, **, *** denote significant coefficients for the 10%, 5% and 1% significance levels, respectively. The right-most column reports the average coefficient of determination, R^2 and $adj - R^2$ in parenthesis, across the cross-sectional regressions.

6.4 Idiosyncratic Industry volatility as characteristic

So far, in Section 6.2 I find that the average industry volatility as factor is not priced, at the 10% significance level, because of the controls for market-wide volatility in addition to the size control. In addition, in Section 6.2 I find that idiosyncratic industry volatility as industry-varying factor is also not priced at the 10% significance levels. In this section, and more extensively in the tables of the web appendix, I investigate if industry volatility is priced as characteristic. I perform Fama-MacBeth regression analyses in order to test hypothesis 3, as explained above and I examine if the magnitude of individual industry volatility, calcuated with the value-weighting scheme, $(IINDvw)$. I present the results in Table 6.

Table 6 has a similar form to the previous Tables 4 and 5. In Panel A, I augment each of the CAPM-FF3-FF5 models with the magnitude of the idiosyncratic industry volatility which varies by industry and I further control for the betas of market-wide volatility, β_{MKTvw}, and the betas of the average idiosyncratic firm volatility within each industry, $\beta_{AIFIRMvw}$, which I also treat as an industry-varying factor. In Panel B, I additionally control for the magnitudes of size and value. In both panels, the t-statistics are adjusted according to Newey-West (1987) with a lag of 5 months and I also include the simple and adjusted coefficients.

In the specifications 2, 5 and 8, of Panel A of Table 6, I find a negative and statitically strong at the 5% significance level relation of the of the risk premium of magnitude of idiosyncratic industry volatility, $IINDvw$, to the stock returns. The risk premium of $IINDvw$ ranges from -7.963×10^3 for the $IINDvw$ CAPM-augmented model, to -7.2×10^3 for the FF3-augmented model and to -6.746×10^3 for the FF5-augmented model. This negative magnitude of the risk premium of $IINDvw$ is consistent with the previous Tables 4 and 5, where I find that the risk premia of the betas of the average industry volatility, β_{INDvw}, and of the idiosyncratic industry volatility, β_{IINDvw}, are negatively associated with the cross-section of stock returns.

In specifications 3, 6 and 9 of Panel A, I also control for the betas of the market-wide volatility, β_{MKTvw}, the average industry volatility, β_{INDvw}, the aggregate average idiosyncratic volatility β_{FIRMvw} and the magnitude of idiosyncratic stock volatility, $IFIRMvw$. Hence, in this table I contrast the characteristics of the stock idiosyncratic $(IFIRMvw)$ and industry idiosyncratic volatility $(IINDvw)$ to the betas of the aggregate average volatility factors, β_{FIRMvw} and β_{INDvw}, respectively. The magnitudes and t-statistics of the risk premia of the baseline models are also consistent with Tables 4 and 5. In specifications 3, 6 and 9, the risk premium of the idiosyncratic stock-level volatility $IFIRMvw$ is estimated with the magnitudes of -0.372×10^3, -0.338×10^3 and -0.314×10^3, respectively, and is statistically very stronger than $IINDvw$, at the 1% significance level.

Considering the descriptive statistics of Table 3, line 3 for $\bar{\tilde{I}}INDvw$, one standard deviation of $IINDvw$ is 14.22. Hence, given the specification 3 of Table 4 for the CAPM augmented model, and the risk premium of $IINDvw$, which is -7.963×10^3, a change of one standard deviation of $IINDvw$ is associated with lower excess returns by approximately -0.11% in a monthly basis. For $IFIRMvw$, although the magnitude of its risk premium is much lower, its standard deviation is much higher, at 1562.37[13] and the associated change in returns is more than 5 times higher than of the magnitude of $IINDvw$, at 0.58% in a monthly basis. The very low coefficient of $IFIRM$ highlights the caution of presenting the results of Fama-MacBeth regression analyses when we include series with different scaling in their units. Had I computed the volatility series based on normal and not in percentage returns, the volatility series would be 1×10^4 lower, and thus the coefficient of $IFIRM$ would be ten thousand times larger. For this reason, I scale the coefficients of $IINDvw$ and $IFIRMvw$ in the table by 1×10^3. Nevertheless, the economic interpretation does not change.

In Panel B, where I also control for the magnitudes of size and value, the risk premium of $IINDvw$ remains statistically significant at 5% in specifications 1 and 3, while it becomes weaker in the rest of the specifications. The magnitudes and statistical significance of the risk premia of the betas of the factors of the baseline models are consistent with the previous tables, except for β_{SMB} which becomes positive in specification 4 an 6, but remains statistically indistinguishable from zero.

Concluding, I find that at the 5% significance level, I reject hypothesis 3, which postulates that idiosyncratic industry volatility is not priced as characteristic, since it is not statistically indistinguishable from zero for the the value-weighted scheme. Moreover, I confirm the strand of literature that finds a strong negative assossiation between the cross-section of stock returns and the stock idiosyncratic volatility (Ang et al. (2006)) as well as the market-wide volatility (Glosten, Jagannathan and Runkle (1983)).

[13] Table 3, line 7.

Panel A

#	$\hat{\lambda}_{\text{intercept}}$	$\hat{\lambda}_{\beta_{MktRF}}$	$\hat{\lambda}_{\beta_{SMB}}$	$\hat{\lambda}_{\beta_{HML}}$	$\hat{\lambda}_{\beta_{RMW}}$	$\hat{\lambda}_{\beta_{CMA}}$	$\hat{\lambda}_{\beta_{INDvw}}$	$\hat{\lambda}_{\text{IINDvw}}(\times 10^3)$	$\hat{\lambda}_{\beta_{MKTvw}}$	$\hat{\lambda}_{\beta_{FIRMvw}}$	$\hat{\lambda}_{\text{IFIRMvw}}(\times 10^3)$	R^2, $\bar{R}^2$ (in %)
1	0.896	-0.104										1.595
	(4.48)***	(-0.817)										(1.569)
2	0.937	-0.098						-7.963				1.859
	(4.69)***	(-0.785)						(2.13)**				(1.805)
3	0.874	-0.061					-0.939	-7.743	-3.403	-2.971	-0.372	3.3
	(4.448)***	(-0.518)					(1.909)*	(2.204)**	(2.203)**	(2.314)**	(2.841)***	(3.142)
4	0.827	-0.083	-0.014	0.147								2.753
	(4.3)***	(-0.762)	(-0.194)	(2.34)**								(2.674)
5	0.873	-0.082	-0.012	0.146				-7.2				2.976
	(4.53)***	(-0.771)	(-0.169)	(2.348)**				(2.077)**				(2.87)
6	0.838	-0.041	0.019	0.136			-0.861	-6.875	-3.271	-2.76	-0.338	3.994
	(4.346)***	(-0.397)	(0.272)	(2.269)**			(1.851)*	(2.058)**	(2.249)**	(2.264)**	(2.959)***	(3.784)
7	0.811	-0.068	-0.012	0.142	-0.009	0.077						3.098
	(4.206)***	(-0.632)	(-0.166)	(2.318)**	(-0.188)	(1.802)*						(2.966)
8	0.857	-0.069	-0.01	0.142	-0.009	0.076		-6.746				3.307
	(4.444)***	(-0.656)	(-0.138)	(2.333)**	(-0.197)	(1.807)*		(2.003)**				(3.149)
9	0.828	-0.032	0.015	0.133	-0.016	0.071	-0.869	-6.61	-3.296	-2.798	-0.314	4.234
	(4.293)***	(-0.304)	(0.223)	(2.291)**	(-0.383)	(1.769)*	(1.796)*	(2.026)**	(2.19)**	(2.226)**	(2.837)***	(3.973)

Panel B

#	$\hat{\lambda}_{\text{intercept}}$	$\hat{\lambda}_{\beta_{MktRF}}$	$\hat{\lambda}_{\beta_{SMB}}$	$\hat{\lambda}_{\beta_{HML}}$	$\hat{\lambda}_{\beta_{RMW}}$	$\hat{\lambda}_{\beta_{CMA}}$	$\hat{\lambda}_{\beta_{INDvw}}$	$\hat{\lambda}_{\text{IINDvw}}(\times 10^3)$	$\hat{\lambda}_{\beta_{MKTvw}}$	$\hat{\lambda}_{\beta_{FIRMvw}}$	$\hat{\lambda}_{\text{IFIRMvw}}(\times 10^3)$	$\hat{\lambda}_{\text{ln.BM}}$	$\hat{\lambda}_{\text{ln.ME}}$	R^2, $\bar{R}^2$ (in %)
1	1.259	0.015						-6.839				0.252	-0.078	3.484
	(3.886)***	(0.133)						(1.986)**				(3.682)***	(1.868)*	(3.33)
2	1.309	0.045					-0.654	-6.397	-2.289	-2.129	-0.653	0.259	-0.085	4.645
	(4.255)***	(0.422)					(1.709)*	(1.926)*	(2.156)**	(2.096)**	(4.036)***	(3.74)***	(2.226)**	(4.34)
3	1.266	0.036	-0.028	0.078				-6.843				0.231	-0.084	4.153
	(4.217)***	(0.339)	(-0.471)	(1.479)				(2.055)**				(3.657)***	(2.283)**	(3.923)
4	1.309	0.055	0.004	0.065			-0.701	-6.12	-2.518	-2.235	-0.632	0.237	-0.089	5.169
	(4.517)***	(0.548)	(0.08)	(1.242)			(1.695)*	(1.892)*	(2.009)**	(2.035)**	(3.981)***	(3.74)***	(2.623)***	(4.79)
5	1.263	0.045	-0.027	0.07	0.018	0.024		-6.29				0.237	-0.084	4.514
	(4.192)***	(0.43)	(-0.489)	(1.355)	(0.454)	(0.613)		(1.942)*				(3.754)***	(2.311)**	(4.208)
6	1.316	0.059	0.002	0.059	0.009	0.018	-0.746	-5.795	-2.562	-2.313	-0.608	0.239	-0.09	5.457
	(4.505)***	(0.579)	(0.04)	(1.16)	(0.244)	(0.471)	(1.661)*	(1.822)*	(1.917)*	(1.99)**	(3.835)***	(3.763)***	(2.657)***	(5.003)

Table 6: *Fama-MacBeth cross-sectional regression analysis (second step) for the value-weighted idiosyncratic industry volatility (IINDvw) as characteristic.* The left-hand side (test or basis assets) are excess returns of individual stocks. The right-hand side are betas of the CAPM-FF3-FF5 factors and the idiosyncratic industry volatility (IINDvw) following Campbell et al. (2001). I use a value-weighting scheme (vw). In Panel A I control for the betas of market volatility (β_{MKTvw}), average industry volatility (β_{INDvw}), aggregate average idiosyncratic firm volatility (β_{FIRMvw}) as factors and idiosyncratic stock volatility ($\beta_{IFIRMvw}$) as characteristic, again with their respective weighting scheme, using exclusively the CRSP database. In Panel B I additionally control for size ($\ln BM$) and value ($\ln ME$), using the merged CRSP/Compustat (CCM) database. The period for the time-series 60-month rolling regressions to estimate the βs is 07:1963–12:2015. The period for the cross-sectional regressions is 08:1968–12:2015. Robust Newey-West (1987) t-statistics with 5 lags are reported in parentheses. *, **, *** denote significant coefficients for the 10%, 5% and 1% significance levels, respectively. The right-most column reports the average coefficient of determination, R^2 and $adj-R^2$ in parenthesis, across the cross-sectional regressions.

6.5 Different SIC coarseness and industry definition

So far in the thesis, I have only found strong support for the alternative of hypothesis 3, that idiosyncratic industry volatility is priced as characteristic. In the previous sections, I used the SIC based classification to divide the market into 49 industries, based on Fama and French (1997). In this section, I explore whether the results differ considering two other industry classifications, in order to explore hypothesis 4.

First, I divide the market into the 10 SIC-based divisions. I follow the SIC-based classification scheme of U. S. Department of Labor and I form the ten divisions of (i) agriculture, forestry, and fishing, (ii) mining, (iii) construction, (iv) manufacturing, (v) transportation, communications, electric, gas, and sanitary services, (vi) wholesale trade, (vii) retail trade, (viii) finance, insurance, and real estate, (ix) services, (x) public administration. I do not assign the unclassified few stocks to an eleventh division so as not to add any bias in the calculation of the volatility series and I create a dataset of 22,880 firms and 2,894,972 monthly observations. Second, I follow Hoberg and Philips (2010, 2015) and I assign the market to 25 Industries, based on their website's provided FIC codes. Hoberg and Philips (2010, 2015) create the FIC categories based on the similarity of textual analysis of firm 10-K product descriptions. Unfortunately, their sample is restricted from October 1996 and excludes a large amount of firms. Although Hoberg and Philips (2010) explain that they capture 97.6% (55,326 firm-year observations) of the CRSP/Compustat database and claim at one point that they do not believe their data induces any bias. However, at a later point their final sample is reduced to 50,104 firm-year observations because they require lagged Compustat data items. Hence, the results should be perceived with caution because the last requirement may have induced some selection-bias. Moreover, I do not assign stocks with missing FIC codes to a 26th industry. I create a dataset of 10,935 firms and 847,509 monthly observations.

To test hypothesis 4, I replicate the calculation of the volatility series and all the previous Fama-MacBeth regresion analyses (second steps) based on the indirect volatility decomposition of Campbell et al. (2001). I present comprehensive results in the web appendix. Table 6 summarizes the results for the SIC-based classification which assigns the stocks to 10 divisions, and Table 7 summarizes the results for the 25 FIC-based industries. Both tables concern the value-weighted scheme.

For both tables, Panels A, B, and C correspond to Tables 4, 5, 6, where I test hypotheses 1, 2 and 3, respectively. Panels A examine the robustness of the average industry volatility as factor for the two different industry classifications. Panels B examine the robustness of the idiosyncratic industry volatility as an industry-varying factor. Last, Panels C examine the robustness of the idiosyncratic industry volatility as characteristic. Moreover, in both Tables and every Panel, in the specifications 3, 6 and 9 I control for the magnitudes of size and value, and I estimate the regressions based on the CRSP/Compustat Merged database (CRSP). The rest of the specifications are estimated using only the CRSP database.

6.5.1 Testing hypothesis 1 for the two classification schemes

Using the SIC-based 10 division classification, Table 6, Panel A, shows that the risk premium of the factor loading of the value-weighted average industry volatility $INDvw$ is not statistically important at the weak 10% significance level. However, the risk premia of the betas of market-wide volatility and the aggregate average stock volatility are negative and statistically important at the 5% significance levels, in specifications 2, 5 and 8. This finding holds for every augmented baseline model when I only augment them with the beta of average industry volatility, β_{INDvw}. When I additionally control for the magnitudes of size and value, in specifications 3, 6 and 9, the significance of the risk premia of β_{MKTvw} and β_{FIRMvw} drops to 5% significance level. Hence, using the SIC-based 10 division classification does not alter the non-rejection of hypothesis 1. Additionally, Panel A, supports the strand of literature which finds a negative relation between the market and aggregate stock idiosyncratic volatility to the stock returns.

Considering the FIC-based 25 industry classification, Table 7 does not change the picture for hypothesis 1 and it is not rejected at the 10% significance level. Last, although I find negative risk premia for the betas of the market-wide volatility and the aggregate stock idiosyncratic volatility they are statistically indistinguishable from zero.

6.5.2 Testing hypothesis 2 for the two classification schemes

Table 6 shows that the risk premium of the beta of the idiosyncratic industry volatility, β_{IINDvw}, is statistically significant at the 10% significance level, in specifications 1, 4 and 7. However, when I augment the baseline models with the betas of the market-wide volatility (β_{MKTvw}) and the average idiosyncratic stock volatility within industry as an industry-varying factor ($\beta_{AIFIRMvw}$), it becomes statistically insignificant. Moreover, when I additionally control for the magnitudes of size and value, it becomes significant again, asserting the potential manifestation of the survivorship bias of the Compustat database. Moreover, the magnitude of the risk premium for β_{IINDvw} loses half of its absolute value in specifications 2-3, 5-6, 8-9, giving support for the confounding relationship with $\beta_{AIFIRMvw}$.

I confirm this relationship with Table 7, Panel B, which concerns the FIC-based 25 industry classification. Specification 5 of the panel, shows that the risk premium of β_{IINDvw} changes from -0.732 to -0.341 in specification 6, in which I augment the FF3 model, albeit statistically indistinguishable from zero. Overall, so far, I find evidence consistent with hypothesis 4.

6.5.3 Testing hypothesis 3 for the two classification schemes

Using the 10 SIC division classification, Table 6, Panel C, shows that the value-weighted magnitude of idiosyncratic industry volatility $IINDvw$ is important for every specification at the 5% significance level. Thus, I reject hypothesis 3 for the SIC-based 10 division classification. Moreover, the risk premia of the betas of the market-wide volatility and the aggregate average stock idiosyncratic volatility remain negative and statistically strong at the 5% significance level, while for the FF3-5 models where I additionally control for the magnitudes of size and value (specification 6 and 9) they become weaker and statistically significant at the 1% significance level.

Turning to the FIC-based 25 industry classification, Table 7, Panel C, indicates that I cannot draw any robust conclusion for any variable. Moreover, the risk premium of the magnitude of idiosyncratic industry volatility with the exception of specification 9, becomes positive in every specification, acquiring the magnitude of 0.002, albeit statistically indistinguishable from 0, with a t-statistic of less than 0.186 in absolute value for every specification. The only exception is the risk premium of the magnitude of value, the logarithm of the book-to-market ratio, which is statistically significant at the 5% significance level for the FF3-augmented model, specification 5, and even stronger, at 1% for the CAPM and FF5-augmented models, specifications 3 and 9.

6.5.4 Interpretation of hypothesis 4

Hypothesis 4, finds support considering the two SIC-based classification, assigning the market to 49 industries or 10 divisions, because the results of hypotheses 1, 2 and 3, do not change.

However, considering the FIC-based classification and assigning stocks to 25 industries changes dramatically the previous clause. Using the FIC-based classification none of the tested variables is robustly significant. The only exception is the risk premium of the magnitude of the book-to-market ratio which is positive an statistically very strong and acquires a value between 0.238 (Table 6, Panel C, specification 9) to 0.28 (Table 6, Panel A, specification 1).

In conclusion, although I caution on the potential selection bias briefly explained in the introduction of this Section, given the results I reject hypothesis 4. Thus, the pricing of industry volatility is not robust against different industry classifications.

6.6 Summary of the main results

I conclude the Empirical Results section with summarising the main results. First, considering the two SIC-based industry classifications and assigning the stocks to 49 industries or 10 divisions, I find support for the literature that finds a negative relation between the market volatility and stock returns (e.g. Glosten, Jagannathan and Runkle (1983), Brandt and Kang (2004)). I also present evidence for a strong negative relation of the three dimensions of the stock idiosyncratic volatility of the stock returns, that is (i) the aggregate average stock idiosyncratic volatility, (ii) the average stock idiosyncratic volatility as an industry-varying factor, and (iii) the stock idiosyncratic volatility as characteristic at the firm level. This finding supports the strand of literature on stock idiosyncratic volatility that also finds a negative relation between stock idiosyncratic volatility and stock returns (i.e. Guo and Savickas (2005) and Ang, Hodrick, Xing, and Zhang (2006, 2009)). However, the above findings are not robust when I consider the FIC-code based classification of Hoberg and Philips (2010) and assign the stocks into 25 industries.

Second, I document that average industry volatility as a risk factor is not priced for the cross-section of stock returns, since it does not survive the controls of market-wide volatility as a risk factor and the magnitude of size, for the SIC-based 49 industry classification, after requiring in my dataset stocks with at least 24 months of observations. Further, the SIC-based 10 division classification and the FIC-based 25 industry classification support the non-pricing of the average industry volatility. Hence, I cannot reject the hypothesis 1 that average industry volatility is not a priced factor for the cross-section of stock returns.

Third, I find that idiosyncratic industry volatility as an industry-varying risk factor is also not priced for the cross-section of stock returns, for any of the additional two industry classifications. Hence, I cannot reject the hypothesis 2 of the thesis.

Fourth, I find that the magnitude of the idiosyncratic industry volatility is priced as characteristic for the cross-section of stock returns for the two SIC-based classifications. However, I do not find support for this claim for the FIC-based classification. Thus, exclusively considering the SIC-based classifications, I reject the hypothesis that idiosyncratic industry volatility is not priced as a characteristic at the 5% level of statistical significance.

Fifth, given the evidence that the idiosyncratic industry volatility seems to be priced as a characteristic for the two SIC-based industry classifications and not for the FIC-based classification, I do not find support for hypothesis 4. Hence, this finding indicates that for pricing industry related factors or characteristics, it might be important to also examine if such pricing relations hold for different industry classification schemes.

SIC 10 divisions

Panel A: IND as factor

#	$\hat{\lambda}_{\text{intercept}}$	$\hat{\lambda}_{\beta_{MktRF}}$	$\hat{\lambda}_{\beta_{SMB}}$	$\hat{\lambda}_{\beta_{HML}}$	$\hat{\lambda}_{\beta_{RMW}}$	$\hat{\lambda}_{\beta_{CMA}}$	$\hat{\lambda}_{\beta_{INDvw}}$	$\hat{\lambda}_{\beta_{MKTvw}}$	$\hat{\lambda}_{\beta_{FIRMvw}}$	$\hat{\lambda}_{\text{ln.BM}}$	$\hat{\lambda}_{\text{ln.ME}}$	R^2, $\bar{R}^2$ (in %)
1	0.866	-0.078					-0.441					1.914
	(4.274)***	(-0.596)					(-1.575)					(1.86)
2	0.843	-0.091					-0.375	-3.235	-3.229			2.48
	(4.248)***	(-0.743)					(-1.55)	(2.07)**	(2.132)**			(2.373)
3	1.171	0.029					-0.253	-2.302	-2.388	0.28	-0.071	3.937
	(3.653)***	(0.262)					(-1.257)	(1.942)*	(1.881)*	(4.016)***	(1.757)*	(3.706)
4	0.798	-0.049	-0.007	0.136			-0.398					2.98
	(4.111)***	(-0.439)	(-0.095)	(2.161)**			(-1.533)					(2.873)
5	0.796	-0.056	-0.004	0.138			-0.329	-3.005	-2.892			3.28
	(4.125)***	(-0.53)	(-0.059)	(2.259)**			(-1.548)	(2.143)**	(2.118)**			(3.121)
6	1.188	0.042	-0.015	0.066			-0.237	-2.328	-2.311	0.254	-0.078	4.489
	(3.965)***	(0.405)	(-0.256)	(1.257)			(-1.277)	(1.888)*	(1.857)*	(3.992)***	(2.144)**	(4.183)
7	0.789	-0.042	-0.005	0.136	-0.014	0.068	-0.411					3.298
	(4.064)***	(-0.375)	(-0.071)	(2.201)**	(-0.308)	(1.603)	(-1.507)					(3.14)
8	0.789	-0.049	-0.003	0.135	-0.007	0.067	-0.343	-3.055	-2.924			3.554
	(4.077)***	(-0.46)	(-0.038)	(2.27)**	(-0.156)	(1.635)	(-1.501)	(2.089)**	(2.056)**			(3.342)
9	1.211	0.044	-0.017	0.062	0.021	0.021	-0.249	-2.316	-2.352	0.255	-0.081	4.787
	(4.014)***	(0.436)	(-0.303)	(1.205)	(0.551)	(0.546)	(-1.266)	(1.853)*	(1.85)*	(3.998)***	(2.239)**	(4.406)

Panel B: $IIND$ as industry-varying factor

#	$\hat{\lambda}_{\text{intercept}}$	$\hat{\lambda}_{\beta_{MktRF}}$	$\hat{\lambda}_{\beta_{SMB}}$	$\hat{\lambda}_{\beta_{HML}}$	$\hat{\lambda}_{\beta_{RMW}}$	$\hat{\lambda}_{\beta_{CMA}}$	$\hat{\lambda}_{\beta_{IINDvw}}$	$\hat{\lambda}_{\beta_{MKTvw}}$	$\hat{\lambda}_{\beta_{AIFIRMvw}}$	$\hat{\lambda}_{\text{ln.BM}}$	$\hat{\lambda}_{\text{ln.ME}}$	R^2, $\bar{R}^2$ (in %)
1	0.905	-0.117					-0.085					1.759
	(4.464)***	(-0.976)					(1.94)*					(1.705)
2	0.904	-0.139					-0.043	-1.592	-1.429			2.161
	(4.525)***	(-1.269)					(-1.601)	(2.136)**	(2.596)***			(2.054)
3	1.239	-0.022					-0.044	-1.231	-1.32	0.263	-0.073	3.651
	(3.84)***	(-0.217)					(1.689)*	(1.887)*	(2.507)**	(3.862)***	(1.833)*	(3.419)
4	0.84	-0.089	-0.016	0.135			-0.075					2.844
	(4.337)***	(-0.884)	(-0.215)	(2.178)**			(1.788)*					(2.737)
5	0.857	-0.103	-0.022	0.126			-0.043	-1.57	-1.331			3.036
	(4.391)***	(-1.108)	(-0.314)	(2.103)**			(1.683)*	(2.189)**	(2.544)**			(2.876)
6	1.249	0.004	-0.039	0.064			-0.049	-1.341	-1.358	0.24	-0.08	4.249
	(4.124)***	(0.048)	(-0.687)	(1.299)			(1.821)*	(1.924)*	(2.562)**	(3.786)***	(2.22)**	(3.942)
7	0.832	-0.083	-0.011	0.132	-0.008	0.075	-0.069					3.157
	(4.303)***	(-0.841)	(-0.15)	(2.189)**	(-0.172)	(1.768)*	(1.683)*					(2.998)
8	0.853	-0.099	-0.02	0.123	-0.002	0.074	-0.038	-1.536	-1.32			3.307
	(4.366)***	(-1.07)	(-0.285)	(2.144)**	(-0.041)	(1.859)*	(-1.525)	(2.175)**	(2.58)**			(3.095)
9	1.263	0.006	-0.037	0.06	0.023	0.031	-0.046	-1.322	-1.314	0.238	-0.083	4.555
	(4.131)***	(0.071)	(-0.679)	(1.276)	(0.652)	(0.856)	(1.698)*	(1.893)*	(2.512)**	(3.73)***	(2.281)**	(4.172)

Panel C: $IIND$ as characteristic

#	$\hat{\lambda}_{\text{intercept}}$	$\hat{\lambda}_{\beta_{MktRF}}$	$\hat{\lambda}_{\beta_{SMB}}$	$\hat{\lambda}_{\beta_{HML}}$	$\hat{\lambda}_{\beta_{RMW}}$	$\hat{\lambda}_{\beta_{CMA}}$	$\hat{\lambda}_{\beta_{INDvw}}$	$\hat{\lambda}_{\text{IINDvw}}$	$\hat{\lambda}_{\beta_{MKTvw}}$	$\hat{\lambda}_{\beta_{FIRMvw}}$	$\hat{\lambda}_{\text{IFIRMvw}}$	$\hat{\lambda}_{\text{ln.BM}}$	$\hat{\lambda}_{\text{ln.ME}}$	R^2, $\bar{R}^2$ (in %)
1	0.978	-0.099						-0.021						1.936
	(4.837)***	(-0.789)						(2.063)**						(1.882)
2	0.915	-0.051					-0.407	-0.021	-3.364	-3.418	0			3.395
	(4.634)***	(-0.429)					(1.712)*	(2.149)**	(2.195)**	(2.325)**	(2.898)***			(3.236)
3	1.338	0.066					-0.27	-0.025	-2.351	-2.465	-0.001	0.272	-0.085	4.758
	(4.237)***	(0.613)					(-1.362)	(2.497)**	(2.025)**	(1.978)**	(4.179)***	(3.99)***	(2.228)**	(4.452)
4	0.917	-0.081	-0.02	0.145				-0.02						3.064
	(4.736)***	(-0.763)	(-0.273)	(2.353)**				(2.048)**						(2.958)
5	0.879	-0.032	0.013	0.132			-0.356	-0.02	-3.094	-3.035	0			4.071
	(4.539)***	(-0.318)	(0.19)	(2.214)**			(1.708)*	(2.089)**	(2.248)**	(2.287)**	(2.929)***			(3.861)
6	1.338	0.068	0.011	0.066			-0.252	-0.025	-2.358	-2.37	-0.001	0.249	-0.088	5.264
	(4.5)***	(0.679)	(0.197)	(1.283)			(-1.38)	(2.514)**	(1.958)*	(1.94)*	(4.093)***	(3.953)***	(2.53)**	(4.884)
7	0.899	-0.069	-0.017	0.142	-0.005	0.07		-0.019						3.387
	(4.65)***	(-0.65)	(-0.239)	(2.354)**	(-0.109)	(1.683)*		(1.975)**						(3.228)
8	0.868	-0.028	0.012	0.131	-0.012	0.061	-0.365	-0.019	-3.115	-3.045	0			4.312
	(4.493)***	(-0.268)	(0.176)	(2.261)**	(-0.284)	(1.517)	(-1.638)	(2.072)**	(2.175)**	(2.205)**	(2.826)***			(4.05)
9	1.355	0.066	0.005	0.063	0.012	0.016	-0.261	-0.024	-2.334	-2.399	-0.001	0.251	-0.089	5.536
	(4.527)***	(0.667)	(0.092)	(1.25)	(0.317)	(0.417)	(-1.355)	(2.486)**	(1.914)*	(1.927)*	(3.969)***	(3.985)***	(2.584)**	(5.081)

Table 6: ***Replication of Tables 4, 5 and 6 for the SIC-based 10 division classification.*** Panel A contains the Fama-MacBeth cross-sectional regression analysis (second step) for the value-weighted average industry volatility (INDvw) as risk factor. Panel B contains the Fama-MacBeth cross-sectional regression analysis (second step) for the value-weighted idiosyncratic industry volatility (IINDvw) as industry-varying risk factor. Panel C contains the Fama-MacBeth cross-sectional regression analysis (second step) for the value-weighted idiosyncratic industry volatility (IINDvw) as characteristic. Specifications 1-2, 4-5, 7-8 are estimated using the CRSP database. Specifications 3, 6, 9 are estimated using the Compustat/CRSP merged (CCM) database. Robust Newey-West (1987) t-statistics with 5 lags are reported in parentheses. *, **, *** denote significant coefficients for the 10%, 5% and 1% significance levels, respectively. The right-most column reports the average coefficient of determination, R^2 and $adj - R^2$ in parenthesis, across the cross-sectional regressions.

FIC 25 industries

Subpanel A: IND as factor

#	$\hat{\lambda}_{\text{intercept}}$	$\hat{\lambda}_{\beta_{MktRF}}$	$\hat{\lambda}_{\beta_{SMB}}$	$\hat{\lambda}_{\beta_{HML}}$	$\hat{\lambda}_{\beta_{RMW}}$	$\hat{\lambda}_{\beta_{CMA}}$	$\hat{\lambda}_{\beta_{INDvw}}$	$\hat{\lambda}_{\beta_{MKTvw}}$	$\hat{\lambda}_{\beta_{FIRMvw}}$	$\hat{\lambda}_{\text{ln.BM}}$	$\hat{\lambda}_{\text{ln.ME}}$	R^2, $\bar{R}^2$ (in %)
1	0.826	0.275					-1.8					1.873
	(1.919)*	(0.969)					(-1.38)					(1.808)
2	0.763	0.257					-1.6	-8.321	-5.565			2.171
	(1.81)*	(0.934)					(-1.309)	(-1.648)	(-1.547)			(2.042)
3	1.321	0.261					-1.379	-7.566	-4.461	0.248	-0.074	3.017
	(1.991)**	(0.973)					(-1.113)	(-1.508)	(-1.228)	(2.502)**	(-1.315)	(2.825)
4	0.813	0.32	0.005	0.147			-1.76					2.307
	(1.98)**	(1.164)	(0.065)	(1.255)			(-1.351)					(2.178)
5	0.814	0.277	0.03	0.174			-1.605	-8.446	-5.557			2.59
	(1.986)**	(1.061)	(0.342)	(1.47)			(-1.308)	(-1.642)	(-1.513)			(2.396)
6	1.457	0.299	-0.026	0.153			-1.39	-7.737	-4.445	0.216	-0.094	3.368
	(2.251)**	(1.146)	(-0.338)	(1.408)			(-1.113)	(-1.513)	(-1.197)	(2.333)**	(1.697)*	(3.112)
7	0.788	0.317	0.016	0.161	-0.091	-0.032	-1.963					2.65
	(1.905)*	(1.159)	(0.215)	(1.386)	(-0.686)	(-0.48)	(-1.438)					(2.457)
8	0.808	0.283	0.021	0.174	-0.058	-0.014	-1.684	-8.47	-5.656			2.886
	(1.947)*	(1.079)	(0.262)	(1.543)	(-0.474)	(-0.23)	(-1.341)	(-1.635)	(-1.517)			(2.629)
9	1.466	0.306	-0.033	0.15	-0.04	-0.019	-1.464	-7.734	-4.562	0.221	-0.095	3.64
	(2.256)**	(1.172)	(-0.46)	(1.441)	(-0.357)	(-0.328)	(-1.149)	(-1.504)	(-1.213)	(2.434)**	(1.754)*	(3.321)

Subpanel B: $IIND$ as industry-varying factor

#	$\hat{\lambda}_{\text{intercept}}$	$\hat{\lambda}_{\beta_{MktRF}}$	$\hat{\lambda}_{\beta_{SMB}}$	$\hat{\lambda}_{\beta_{HML}}$	$\hat{\lambda}_{\beta_{RMW}}$	$\hat{\lambda}_{\beta_{CMA}}$	$\hat{\lambda}_{\beta_{IINDvw}}$	$\hat{\lambda}_{\beta_{MKTvw}}$	$\hat{\lambda}_{\beta_{AIFIRMvw}}$	$\hat{\lambda}_{\text{ln.BM}}$	$\hat{\lambda}_{\text{ln.ME}}$	R^2, $\bar{R}^2$ (in %)
1	0.88	0.226					-0.713					1.712
	(2.059)**	(0.9)					(1.897)*					(1.648)
2	0.953	0.127					-0.323	-3.57	-2.136			1.907
	(2.211)**	(0.589)					(-1.498)	(1.879)*	(1.907)*			(1.777)
3	1.482	0.14					-0.242	-2.991	-1.462	0.227	-0.075	2.788
	(2.144)**	(0.675)					(-1.149)	(-1.645)	(-1.295)	(2.297)**	(-1.32)	(2.596)
4	0.878	0.273	-0.019	0.12			-0.732					2.146
	(2.137)**	(1.149)	(-0.224)	(1.097)			(2.01)**					(2.017)
5	0.983	0.166	-0.014	0.097			-0.341	-3.667	-2.138			2.311
	(2.351)**	(0.815)	(-0.164)	(0.944)			(1.769)*	(1.917)*	(1.96)*			(2.117)
6	1.607	0.19	-0.055	0.08			-0.27	-3.117	-1.411	0.2	-0.096	3.121
	(2.385)**	(0.943)	(-0.761)	(0.871)			(-1.358)	(1.675)*	(-1.263)	(2.171)**	(1.702)*	(2.865)
7	0.872	0.249	-0.007	0.131	-0.067	-0.037	-0.799					2.488
	(2.119)**	(1.083)	(-0.097)	(1.239)	(-0.545)	(-0.561)	(2.232)**					(2.295)
8	0.976	0.15	-0.01	0.104	-0.028	-0.028	-0.397	-3.563	-1.945			2.597
	(2.314)**	(0.752)	(-0.129)	(1.063)	(-0.251)	(-0.478)	(2.031)**	(1.873)*	(1.766)*			(2.339)
9	1.606	0.18	-0.053	0.082	-0.018	-0.031	-0.314	-3.017	-1.266	0.204	-0.095	3.369
	(2.382)**	(0.912)	(-0.792)	(0.938)	(-0.18)	(-0.549)	(-1.557)	(-1.626)	(-1.135)	(2.262)**	(1.718)*	(3.049)

Subpanel C: $IIND$ as characteristic

#	$\hat{\lambda}_{\text{intercept}}$	$\hat{\lambda}_{\beta_{MktRF}}$	$\hat{\lambda}_{\beta_{SMB}}$	$\hat{\lambda}_{\beta_{HML}}$	$\hat{\lambda}_{\beta_{RMW}}$	$\hat{\lambda}_{\beta_{CMA}}$	$\hat{\lambda}_{\beta_{INDvw}}$	$\hat{\lambda}_{\text{IINDvw}}$	$\hat{\lambda}_{\beta_{MKTvw}}$	$\hat{\lambda}_{\beta_{FIRMvw}}$	$\hat{\lambda}_{\text{IFIRMvw}}$	$\hat{\lambda}_{\text{ln.BM}}$	$\hat{\lambda}_{\text{ln.ME}}$	R^2, $\bar{R}^2$ (in %)
1	0.924	0.237						0.002						1.927
	(2.212)**	(0.885)						(0.186)						(1.862)
2	0.834	0.263					-1.675	0.002	-8.48	-5.787	0			2.879
	(2.05)**	(0.978)					(-1.38)	(0.182)	(1.692)*	(-1.624)	(-0.661)			(2.687)
3	1.5	0.269					-1.454	0	-7.634	-4.666	0	0.259	-0.088	3.661
	(2.321)**	(1.023)					(-1.191)	(0.035)	(-1.543)	(-1.304)	(-0.943)	(2.684)***	(-1.624)	(3.406)
4	0.924	0.28	-0.003	0.152				0.001						2.351
	(2.311)**	(1.066)	(-0.04)	(1.369)				(0.109)						(2.222)
5	0.898	0.278	0.032	0.183			-1.657	0.002	-8.526	-5.724	0			3.276
	(2.279)**	(1.088)	(0.379)	(1.588)			(-1.372)	(0.124)	(1.688)*	(-1.588)	(-0.567)			(3.02)
6	1.651	0.304	-0.026	0.161			-1.446	0	-7.758	-4.605	0	0.228	-0.109	4.004
	(2.62)***	(1.191)	(-0.344)	(1.507)			(-1.182)	(0.005)	(-1.55)	(-1.268)	(-0.917)	(2.529)**	(2.023)**	(3.686)
7	0.896	0.273	0.008	0.167	-0.071	-0.027		0.001						2.696
	(2.228)**	(1.053)	(0.109)	(1.513)	(-0.57)	(-0.413)		(0.109)						(2.503)
8	0.898	0.28	0.022	0.182	-0.058	-0.011	-1.733	0.001	-8.492	-5.796	0			3.551
	(2.244)**	(1.093)	(0.29)	(1.656)*	(-0.492)	(-0.182)	(-1.402)	(0.084)	(1.671)*	(-1.586)	(-0.461)			(3.232)
9	1.661	0.308	-0.034	0.157	-0.041	-0.017	-1.514	-0.001	-7.707	-4.698	0	0.233	-0.109	4.26
	(2.621)***	(1.204)	(-0.483)	(1.538)	(-0.374)	(-0.299)	(-1.213)	(-0.051)	(-1.533)	(-1.279)	(-0.814)	(2.642)***	(2.072)**	(3.88)

Table 7: ***Replication of Tables 4, 5 and 6 for the FIC-based 25 industry classification.*** Panel A contains the Fama-MacBeth cross-sectional regression analysis (second step) for the value-weighted average industry volatility (INDvw) as risk factor. Panel B contains the Fama-MacBeth cross-sectional regression analysis (second step) for the value-weighted idiosyncratic industry volatility (IINDvw) as industry-varying risk factor. Panel C contains the Fama-MacBeth cross-sectional regression analysis (second step) for the value-weighted idiosyncratic industry volatility (IINDvw) as characteristic. Specifications 1-2, 4-5, 7-8 are estimated using the CRSP database. Specifications 3, 6, 9 are estimated using the Compustat/CRSP merged (CCM) database. Robust Newey-West (1987) t-statistics with 5 lags are reported in parentheses. *, **, *** denote significant coefficients for the 10%, 5% and 1% significance levels, respectively. The right-most column reports the average coefficient of determination, R^2 and $adj - R^2$ in parenthesis, across the cross-sectional regressions.

7 Robustness checks

In this section of the robustness checks, I mainly perform three robustness checks for the conclusion of the previous section that I reject hypothesis 3, for the SIC-based industry classification forming 49 industries as in Fama and French (1997). First, I adapt the methodology of Ang et al. (2006) and I test portfolios formed by sorting on $IINDvw$, as calculated by the indirect decomposition method of Campbell et al. (2001). Second, I continue by conducting a second similar robustness check, but this time using the direct decomposition and calculating the idiosyncratic industry volatility with respect to the Fama-French three-factor model, by using industry excess returns as the independent variable. Third, I examine if the pricing of idiosyncratic industry volatility is sensitive to requiring a larger number of month as a minimum for a stock to be included in the regression dataset. Last, I conclude the robustness checks by addressing the concern that the aggregate average industry volatility, $INDvw$ has high auto correlation of first order and I repeat the analysis of Section 6.2. However, as the dependent volatility variables for the second step of the Fama-MacBeth regressions, I use the betas of the innovations, instead of the magnitudes, of the volatility series. For every robustness check, I use the SIC-based 49 industry classification of Fama and French (1997).

7.1 Testing hypothesis 3 forming portfolios sorted on idiosyncratic industry volatility

In this section, I adapt the study of Ang et al. (2006, section II) to an industry level. As in Ang et al. (2006), if idiosyncratic industry volatility ($IINDvw$) is not accounted for by asset pricing models as a component of systematic risk, the asset pricing models would misprice portfolios sorted on $IINDvw$.

Each month, I sort stocks into quintile portfolios based on their idiosyncratic industry volatility ($IINDvw$) of the past month, and I hold these value-weighted portfolios for 1 month (I rebalance them in a monthly basis). As weight, I use the capitalisation of the previous month. As in Ang et al. (2006), this procedure corresponds to a $L = 1/M = 0/N = 1$ trading strategy of Jegadeesh and Titman (1993) but for value-weighted portfolios, where L is the estimation period of the $IINDvw$, M is the waiting period and N is the holding period. I use the merged CRSP/CCM dataset since I want the results to be comparable with Table VI of Ang et al. (2006), who also present the mean book-to-market ratio for each portfolio. Last, I also form a spread portfolio by subtracting the returns of portfolio 1 from portfolio 5.

A small problem with this approach when it is adapted to an industry level is that idiosyncratic industry volatility does not vary by firm, but by industry. Hence, after sorting the stocks by their $IINDvw$, it might be the case that adjacently ranked stocks, most probably of the same industry, have the same magnitude of $IINDvw$, but should be assigned to different quintiles. In order to address this problem, I sort the stocks within each industry based on their size, which varies, in general by stock, in an ascending order. In untabulated results, I find that sorting the stocks by descending order based on their size, or by ascending or descending order by their book-to-market ratio or any combination thereof, does not change the resulting resulting tables, apart from some insignificant digits.

Table 8 presents the results and contains three panels with different screening. Panel A includes the whole sample, Panel B excludes stocks with less than 17 daily observations in a given month and finally, Panel C is formed exclusively considering NYSE stocks, so as to reduce the concern of drawing conclusionon datasets with small stocks. However, as Ang et al. notice, this concern is not completely eliminated since NYSE also includes some small stocks.

According to Panel A, Portfolio 1 (low $IINDvw$) has a mean return of 0.89% in a monthly basis and Portfolio 5 (high $IINDvw$) a mean return of 0.97%. Unlike Ang et al. (2006), Panels A, B and C of Table 8 show that there is not an abrupt return drop from Portfolio 1 to Portfolio 5.p For example, they find that their 4th portfolio has a mean return of 0.87 and the 5th a mean return of -0.02, but in none of the Panels of Table 8 there exists such a drop.

Next, Panel A includes every stock in the sample without any screening, it seems that the alpha of the FF5 model is -0.387, yielding the lowest mispricing among the three baseline models. In Panel B, Table 8 shows similar patterns to the patterns of Panel A. However, in Panel C, which concern only NYSE stocks, the mispricing of all the three baseline models is higher by about 20%-40%. The FF3 model yields an alpha of -0.551 and FF5 an alpha of -0..516. The different screening of the three panels seems not to affect the statistical significance of the alphas for the CAPM, FF3 and FF5 models for the spread portfolios, which is very strong and I cannot reject the mispricing of the respective three baseline models at the 1% level of statistical significance. All the three models are unable to price the spread portfolios and so an investor who sells the spread portfolio from stocks sorted on idiosyncratic stock volatility could gain around 0.4 to 0.5% in a monthly basis. This finding supports the alternative of hypothesis 3, that idiosyncratic industry volatility is priced as characteristic. I continue the robustness checks by applying the same methodology but on recalculating the idiosyncratic industry volatility based on the direct decomposition method.

7.2 Direct volatility decomposition

Thus far in the thesis, I find strong evidence that idiosyncratic industry volatility is priced as a characteristic for industries defined in the two SIC-based classifications schemes, but not for the FIC-based industry classification. For additional robustness of whether the idiosyncratic industry volatility is priced as characteristic, I calculate the idiosyncratic volatility with the direct decomposition, as opposed to the direct decomposition described in the Section 4.2. I decompose volatility as in Ang et al. (2006), Section II, adapting their methodology to an industry level. I create the individual industry volatility and individual firm volatility series relative to the FF3 model. Each month, I run

$$R^e_{t,i} = \alpha_i + \beta_{MktRf,i} MktRf_t + \beta_{SMB,i} SMB_t + \beta_{HML,i} HML_t + \epsilon_{t,i} \tag{7.1}$$

and I define idiosyncratic risk as $\sqrt{var(\epsilon_{t,i})}$. For the idiosyncratic firm volatility, I use the stock returns, and for the idiosyncratic industry volatility the value-weighted industry returns, for the 49 industries based on the SIC classification described in Section 5. Next, in a similar manner to Ang et al. (2006) and Section 6.4 of the thesis, I sort stocks according to their direct idiosyncratic volatility, exactly as I did for Table 8, and I create Table 9.

Table 9, effectively replicates Panel B of Table 8, using the direct decomposition method for calculating the idiosyncratic industry volatility. The two decomposition methods form quintile and spread portfolios with similar market share, size and book-to-market ratio characteristics. The only difference is that of the second quintile Portfolio, which for the indirect decomposition produces a positive CAPM Alpha but for the direct decomposition a negative CAPM Alpha, both insignificant. The Newey-West (1987) t-statistics of the spread portfolio of Table 9 are highly significant at the 1% significance level and both the CAPM and FF3 Alphas are about -0.48&, almost exactly replicating the corresponding Alphas of Panel B of Table 8. Concluding this particular robustness check, I reject hypothesis 3, that idiosyncratic industry volatility is not priced as characteristic at the 1% level of statistical significance.

Panel A: whole sample

Portfolio	Mean	Std. Dev.	% Mkt. Share	Size	B/M	CAPM Alpha	FF3 Alpha	FF5 Alpha
1	0.91	4.37	19.35	4.87	0.9	0.068	0.042	0.028
						(0.908)	(0.594)	(0.391)
2	0.9	4.6	20.46	4.79	0.84	0.027	−0.02	−0.09
						(0.398)	(−0.268)	(−1.217)
3	0.94	4.81	19.89	4.69	0.85	0.044	−0.004	−0.029
						(0.513)	(−0.052)	(−0.35)
4	0.81	5.15	19.42	4.65	0.84	−0.128	−0.134	−0.154
						(−1.582)	(−1.59)	(−1.833)
5	0.95	5.77	20.87	4.64	0.82	−0.025	−0.063	0.009
						(−0.266)	(−0.647)	(0.098)
5 − 1	0.04	3.63				−0.496	−0.505	−0.42
						(−3.838)	(−3.899)	(−3.238)

Panel B: excluding stocks with less than 17 daily observations in a month

Portfolio	Mean	Std. Dev.	% Mkt. Share	Size	B/M	CAPM Alpha	FF3 Alpha	FF5 Alpha
1	0.92	4.36	19.39	4.88	0.9	0.06	0.035	0.021
						(0.805)	(0.49)	(0.294)
2	0.92	4.59	20.49	4.79	0.84	0.029	−0.017	−0.086
						(0.439)	(−0.226)	(−1.162)
3	0.94	4.77	19.88	4.69	0.85	0.028	−0.027	−0.056
						(0.342)	(−0.343)	(−0.713)
4	0.86	5.14	19.4	4.66	0.84	−0.093	−0.091	−0.114
						(−1.144)	(−1.047)	(−1.319)
5	0.99	5.75	20.84	4.65	0.82	−0.005	−0.039	0.028
						(−0.055)	(−0.388)	(0.277)
5 − 1	0.07	3.64				−0.468	−0.475	−0.395
						(−3.565)	(−3.564)	(−2.961)

Panel C: sample restricted to NYSE stocks

Portfolio	Mean	Std. Dev.	% Mkt. Share	Size	B/M	CAPM Alpha	FF3 Alpha	FF5 Alpha
1	0.9	4.21	17.89	6.33	0.91	0.084	0.017	−0.048
						(0.922)	(0.211)	(−0.61)
2	0.92	4.38	20.37	6.34	0.85	0.08	0.014	−0.094
						(1.034)	(0.181)	(−1.211)
3	0.87	4.61	20.09	6.28	0.84	−0.001	−0.073	−0.161
						(−0.012)	(−0.988)	(−2.183)
4	0.96	4.93	20.57	6.26	0.84	0.064	−0.015	−0.124
						(0.676)	(−0.181)	(−1.453)
5	0.94	5.34	21.08	6.26	0.82	0.005	−0.089	−0.115
						(0.054)	(−1.021)	(−1.32)
5 − 1	0.04	3.59				−0.481	−0.506	−0.469
						(−3.715)	(−4.015)	(−3.719)

Table 8: Portfolios sorted on idiosyncratic industry volatility, based on the indirect decomposition method. I construct five quintile portfolios based on the past month's value-weighted idiosyncratic industry volatility, $IINDvw$. The returns of portfolio 1 (5) are value-weighted, based on Market Equity obtained from the Compustat/CRSP merged database (CCM). The mean and standard deviation descriptive statistics apply to raw normal and not excess returns. The Market Share, is calculated based on the Market Equity (size) of every stock over the course of the portfolio's history. Similarly, Size reports the average natural logarithm of the stocks' Market Equity and B/M is the average book-to-market ratio. I form the spread portfolio "5-1" subtracting the returns of portfolio 1 from portfolio 5 in a monthly basis. For the three, CAPM FF3-5, specifications Alphas are the intercept coefficients of time-series regressions of the portfolios' excess returns on their respective factors. The t-statistics follow Newey-West (1987) with a lag of 5 periods (months). The time-series regressions concern the period 08:1963–12:2015
Panel A includes the whole sample. Panel B excludes stock-months with less than 17 daily observations. Panel C is restricted to NYSE stocks, only.

Panel A: whole sample

Portfolio	Mean	Std. Dev.	% Mkt. Share	Size	B/M	CAPM Alpha	FF3 Alpha	FF5 Alpha
1	0.92	4.24	16.51	4.78	0.89	0.093	0.023	−0.028
						(1.111)	(0.292)	(−0.356)
2	0.85	4.67	20.35	4.79	0.84	−0.034	−0.054	−0.104
						(−0.454)	(−0.677)	(−1.314)
3	0.85	4.89	20.39	4.72	0.85	−0.07	−0.068	−0.094
						(−1.066)	(−0.992)	(−1.371)
4	0.9	5.16	20.97	4.72	0.85	−0.032	−0.057	−0.017
						(−0.369)	(−0.641)	(−0.195)
5	0.97	5.62	21.78	4.65	0.83	0.008	−0.058	0.014
						(0.085)	(−0.654)	(0.163)
5 − 1	0.05	3.56				−0.487	−0.481	−0.359
						(−3.772)	(−4.008)	(−2.996)

Panel B: sample restricted to NYSE stocks

Portfolio	Mean	Std. Dev.	% Mkt. Share	Size	B/M	CAPM Alpha	FF3 Alpha	FF5 Alpha
1	0.87	4.07	16.33	6.31	0.92	0.091	−0.014	−0.105
						(0.983)	(−0.176)	(−1.282)
2	0.88	4.36	20.6	6.34	0.84	0.041	−0.017	−0.136
						(0.503)	(−0.208)	(−1.683)
3	0.86	4.73	21.5	6.31	0.84	−0.038	−0.09	−0.184
						(−0.501)	(−1.256)	(−2.566)
4	0.91	4.86	20.54	6.28	0.84	0.015	−0.039	−0.113
						(0.191)	(−0.493)	(−1.448)
5	0.92	5.37	21.03	6.23	0.83	−0.011	−0.136	−0.15
						(−0.108)	(−1.48)	(−1.636)
5 − 1	0.05	3.59				−0.504	−0.522	−0.446
						(−3.956)	(−4.187)	(−3.581)

Table 9: I construct five quintile portfolios based on the past month's value-weighted idiosyncratic industry volatility calculated with the direct decomposition. The returns of portfolio 1 (5) are value-weighted, based on Market Equity obtained from the Compustat/CRSP merged database (CCM), for stocks with at least 17 daily observations in a month. The mean and standard deviation descriptive statistics apply to raw normal and not excess returns. The Market Share is calculated based on the Market Equity (size) of every stock over the course of the portfolio's history. Similarly, Size reports the average natural logarithm of the stocks' Market Equity and B/M is the average book-to-market ratio. I form the spread portfolio "5-1" subtracting the returns of portfolio 1 from portfolio 5 in a monthly basis. For the three, CAPM FF3-5, specifications Alphas are the intercept coefficients of time-series regressions of the portfolios' excess returns on their respective factors. The t-statistics follow Newey-West (1987) with a lag of 5 periods (months). The time-series regressions concern the period 08:1963–12:2015

7.3 Increasing the requirement of the minimum monthly observations

In Section 6.3, I test hypothesis 2 to explore whether idiosyncratic industry volatility is priced as an industry-varying risk factor. When I use the Compustat database for controlling the relation of betas of the idiosyncratic industry volatility to the stock returns with the magnitudes of size and value, I find that there is a marginally statistically strong relation in specification 2, 4 and 6 of Table 6, Panel B. This contrasts the finding of specifications 2, 4 and 6 of Table 6, Panel A, where I do not find a statistically significant relation when I use only the CRSP database. Given the observations of Duffee(1995), that Compustat database includes a high percentage of firms with long history relative to the CRSP database, I conjecture that perhaps there is a survivorship bias in establishing a relation of the idiosyncratic industry volatility as an industry varying factor to the stock returns.

Although I do not find confirmation for the aforementioned finding when I test hypothesis 3 in Section 6.4, in this section I proceed to an additional test. I test whether the pricing of idiosyncratic industry volatility as characteristic is sensitive to changing the minimum monthly observations requirement for the stocks included in the regression dataset. As I explain in Section 4.1, I require at least 24 months of observations for a stock to be included in the regression dataset for the Fama-MacBeth cross-sectional analyses. Here, I require at least 48 months of monthly data for each stock. Both Panels of Table 10 replicate the two Panels of Table 6, but Table 10 requires at least 48 months for a stock to bee included in the regression dataset. In Panel A, I find weak support for the pricing of the idiosyncratic industry volatility ($IINDvw$) as characteristic, at the marginal 10% level of statistical significance. This finding, contrasts Table 6, where I reject hypothesis 3 at the 5% significance level. However, in Panel B, in specifications 2, 5 and 6 the statistical significance of idiosyncratic industry volatility disappears. In specification 2, when I augment the CAPM baseline model, and I control for the betas of average industry volatility, market-wide volatility, aggregate average firm volatility and idiosyncratic firm volatility, the risk premium of $IINDvw$ becomes statistically indistinguishable from zero. The same applies for specifications 5 and 6 where I additionally control for size and value. This finding does not seem to affect the strong negative risk premium of idiosyncratic stock volatility as characteristic ($IFIRM$), which remains statistically strong at the 1% level of statistical significance. Hence, I conclude that the negative pricing of idiosyncratic volatility, is potentially biased by stocks with short age.

Panel A

#	$\hat{\lambda}_{\text{intercept}}$	$\hat{\lambda}_{\beta_{MktRF}}$	$\hat{\lambda}_{\beta_{SMB}}$	$\hat{\lambda}_{\beta_{HML}}$	$\hat{\lambda}_{\beta_{RMW}}$	$\hat{\lambda}_{\beta_{CMA}}$	$\hat{\lambda}_{\beta_{INDvw}}$	$\hat{\lambda}_{\text{IINDvw}}$	$\hat{\lambda}_{\beta_{MKTvw}}$	$\hat{\lambda}_{\beta_{FIRMvw}}$	$\hat{\lambda}_{\text{IFIRMvw}}$	R^2, $\bar{R}^2$ (in %)
1	0.9	-0.084										1.722
	(4.944)***	(-0.595)										(1.69)
2	0.934	-0.078						-0.007				2.022
	(5.131)***	(-0.564)						(1.848)*				(1.958)
3	0.858	-0.032					-0.959	-0.007	-3.764	-3.295	0	3.785
	(4.787)***	(-0.244)					(1.864)*	(1.962)*	(2.27)**	(2.383)**	(3.017)***	(3.596)
4	0.816	-0.067	0.018	0.152								3.062
	(4.697)***	(-0.567)	(0.223)	(2.202)**								(2.967)
5	0.859	-0.067	0.02	0.152				-0.006				3.314
	(4.92)***	(-0.573)	(0.244)	(2.216)**				(1.838)*				(3.188)
6	0.809	-0.013	0.062	0.154			-1.006	-0.006	-3.906	-3.366	0	4.558
	(4.643)***	(-0.109)	(0.821)	(2.277)**			(1.909)*	(1.802)*	(2.259)**	(2.383)**	(3.205)***	(4.308)
7	0.805	-0.053	0.014	0.149	-0.01	0.082						3.488
	(4.668)***	(-0.442)	(0.17)	(2.213)**	(-0.214)	(1.739)*						(3.33)
8	0.849	-0.054	0.015	0.15	-0.01	0.081		-0.006				3.724
	(4.91)***	(-0.459)	(0.193)	(2.231)**	(-0.205)	(1.736)*		(1.806)*				(3.535)
9	0.807	-0.006	0.055	0.151	-0.019	0.075	-1.013	-0.006	-3.921	-3.386	0	4.868
	(4.658)***	(-0.053)	(0.736)	(2.288)**	(-0.416)	(1.644)	(1.862)*	(1.839)*	(2.202)**	(2.34)**	(3.118)***	(4.556)

Panel B

#	$\hat{\lambda}_{\text{intercept}}$	$\hat{\lambda}_{\beta_{MktRF}}$	$\hat{\lambda}_{\beta_{SMB}}$	$\hat{\lambda}_{\beta_{HML}}$	$\hat{\lambda}_{\beta_{RMW}}$	$\hat{\lambda}_{\beta_{CMA}}$	$\hat{\lambda}_{\beta_{INDvw}}$	$\hat{\lambda}_{\text{IINDvw}}$	$\hat{\lambda}_{\beta_{MKTvw}}$	$\hat{\lambda}_{\beta_{FIRMvw}}$	$\hat{\lambda}_{\text{IFIRMvw}}$	$\hat{\lambda}_{\text{ln.BM}}$	$\hat{\lambda}_{\text{ln.ME}}$	R^2, $\bar{R}^2$ (in %)
1	1.267	0.006						-0.006				0.212	-0.079	3.972
	(4.389)***	(0.041)						(1.69)*				(3.166)***	(2.063)**	(3.754)
2	1.278	0.065					-0.812	-0.006	-2.982	-2.648	-0.001	0.223	-0.083	5.442
	(4.721)***	(0.495)					(-1.615)	(-1.639)	(1.85)*	(1.951)*	(3.09)***	(3.317)***	(2.434)**	(5.013)
3	1.211	0.041	-0.011	0.087				-0.006				0.194	-0.076	4.702
	(4.564)***	(0.335)	(-0.162)	(1.398)				(1.853)*				(3.131)***	(2.298)**	(4.378)
4	1.251	0.085	0.018	0.082			-0.842	-0.006	-3.107	-2.74	-0.001	0.202	-0.084	6.01
	(4.942)***	(0.697)	(0.282)	(1.346)			(1.653)*	(1.698)*	(1.88)*	(1.993)**	(3.066)***	(3.24)***	(2.734)***	(5.477)
5	1.234	0.045	-0.023	0.085	0.012	0.015		-0.005				0.203	-0.08	5.148
	(4.71)***	(0.368)	(-0.346)	(1.388)	(0.289)	(0.318)		(-1.614)				(3.29)***	(2.45)**	(4.716)
6	1.264	0.084	0.007	0.079	0.003	0.007	-0.837	-0.005	-3.148	-2.726	-0.001	0.208	-0.085	6.384
	(5.025)***	(0.687)	(0.111)	(1.311)	(0.078)	(0.163)	(-1.617)	(-1.519)	(1.875)*	(1.959)*	(2.952)***	(3.365)***	(2.81)***	(5.746)

Table 10: ***Fama-MacBeth regression analysis (second step) for the value-weighted individual industry volatility (IINDvw) as characteristic, controlling for Size and Book-to-Market ratio, requiring at least 48 months of observations.*** The left-hand side (test or basis assets) are excess returns of individual stocks. The right-hand side are betas of CAPM-FF3-FF5 factors and the individual industry volatility (IIND) following Campbell et al. (2001). I use a value weighting scheme (vw). In Panel A I control for market volatility (MKT), idiosyncratic industry volatility (IND) as factor and idiosyncratic firm volatility (IFIRM) as characteristic, again with their respective weighting scheme, using exclusively the CRSP database. In Panel B I additionally control for size and value, using the merged CRSP/Compustat (CCM) database. The period for the time-series 60-month rolling regressions to estimate the βs is 07:1963–12:2015. The period for the cross-sectional regressions is 08:1968–12:2015. Robust Newey-West (1987) t-statistics with 5 lags are reported in parentheses. *, **, *** denote significant coefficients for the 10%, 5% and 1% significance levels, respectively. The last column reports the average coefficient of determination, R^2 and $adj-R^2$ in parenthesis, across the cross-sectional regressions.

7.4 Innovations of the average industry volatility

One concern on the pricing of the average industry volatility is that the volatility series have a relatively high first order autocorrelation which is at 0.80 and 0.77 for the value-weighted $INDvw$ and the equally-weighted $INDew$ during 07:1963–12:2015 period, but 0.43 and 0.58 for the 07:1963–12:1997 period, respectively. Ang et al. (2006) use the VIX index as a proxy for aggregate volatility risk report a first-order autocorrelation of 0.94 for the VIX index and they use first differences to alleviate this issue. Similarly, I do the same for the aggregate volatility series studied in Section 6.2.

Table 11, Panel A augments the CAPM, FF3, and FF5 models with the innovations on the three volatility series for the value-weighting scheme, $\Delta INDvw$, $\Delta MKTvw$, and $\Delta FIRMvw$, that is the average industry volatility, the market-wide volatility and the aggregate average firm volatility, respectively. Panel A indicates that innovations of the average industry volatility is not a priced factor for the CAPM and FF3 augmented baseline models. However, specifications 8 and 9 show that it is a priced factor for the cross-section of stock returns at the marginal significance level of 10% for the augmented FF5 model, when I control for innovations on the market-wide volatility and the aggregate average firm volatility. Innovations on average firm volatility seem significant for all the three models at the 5% significance levels. Nevertheless, in Panel B where I additionally control for size and value as characteristics, I find that innovations on average industry volatility and firm volatility are not significant and they do not survive the size and value controls. Although I do not find a completely robust relation for any of the volatility variables, Table 11 indicates that the average industry volatility, and more prominently the average firm volatility, is not a component that should be completely ignored.

Panel A

#	$\hat{\lambda}_{\text{intercept}}$	$\hat{\lambda}_{\beta_{MktRF}}$	$\hat{\lambda}_{\beta_{SMB}}$	$\hat{\lambda}_{\beta_{HML}}$	$\hat{\lambda}_{\beta_{RMW}}$	$\hat{\lambda}_{\beta_{CMA}}$	$\hat{\lambda}_{\beta_{\Delta INDvw}}$	$\hat{\lambda}_{\beta_{\Delta MKTvw}}$	$\hat{\lambda}_{\beta_{\Delta FIRMvw}}$	R^2, $\bar{R}^2$ (in %)
1	0.896	-0.104								1.595
	(5.838)***	(-0.825)								(1.569)
2	0.891	-0.102					-0.087			1.781
	(5.789)***	(-0.826)					(-0.682)			(1.727)
3	0.847	-0.097					-0.103	-0.501	-0.563	2.088
	(5.656)***	(-0.806)					(-0.833)	(-1.211)	(1.858)*	(1.981)
4	0.827	-0.083	-0.014	0.147						2.753
	(5.731)***	(-0.797)	(-0.195)	(2.049)**						(2.674)
5	0.828	-0.081	-0.015	0.146			-0.17			2.886
	(5.732)***	(-0.784)	(-0.21)	(2.053)**			(-1.497)			(2.78)
6	0.807	-0.072	-0.014	0.145			-0.186	-0.597	-0.69	3.106
	(5.603)***	(-0.703)	(-0.186)	(2.037)**			(-1.643)	(-1.62)	(2.301)**	(2.947)
7	0.811	-0.068	-0.012	0.142	-0.009	0.077				3.098
	(5.626)***	(-0.663)	(-0.166)	(2.044)**	(-0.169)	(1.6)				(2.966)
8	0.81	-0.068	-0.012	0.142	-0.013	0.076	-0.207			3.219
	(5.618)***	(-0.666)	(-0.164)	(2.055)**	(-0.255)	(1.595)	(1.8)*			(3.061)
9	0.792	-0.056	-0.011	0.138	-0.013	0.074	-0.199	-0.612	-0.719	3.424
	(5.489)***	(-0.554)	(-0.157)	(2.002)**	(-0.249)	(1.59)	(1.747)*	(1.658)*	(2.398)**	(3.213)

#	$\hat{\lambda}_{\text{intercept}}$	$\hat{\lambda}_{\beta_{MktRF}}$	$\hat{\lambda}_{\beta_{SMB}}$	$\hat{\lambda}_{\beta_{HML}}$	$\hat{\lambda}_{\beta_{RMW}}$	$\hat{\lambda}_{\beta_{CMA}}$	$\hat{\lambda}_{\beta_{\Delta INDvw}}$	$\hat{\lambda}_{\beta_{\Delta MKTvw}}$	$\hat{\lambda}_{\beta_{\Delta FIRMvw}}$	$\hat{\lambda}_{\text{ln.BM}}$	$\hat{\lambda}_{\text{ln.ME}}$	R^2, $\bar{R}^2$ (in %)
1	1.212	0.017					0.004			0.25	-0.077	3.413
	(4.431)***	(0.144)					(0.039)			(3.291)***	(-1.167)	(3.259)
2	1.181	0.029					0.002	-0.315	-0.17	0.249	-0.076	3.681
	(4.392)***	(0.258)					(0.018)	(-0.873)	(-0.592)	(3.356)***	(-1.184)	(3.45)
3	1.227	0.033	-0.03	0.075			-0.058			0.23	-0.083	4.071
	(5.128)***	(0.319)	(-0.453)	(1.113)			(-0.53)			(3.369)***	(-1.489)	(3.84)
4	1.207	0.043	-0.025	0.072			-0.078	-0.432	-0.342	0.235	-0.082	4.313
	(5.079)***	(0.423)	(-0.384)	(1.062)			(-0.704)	(-1.203)	(-1.184)	(3.506)***	(-1.501)	(4.006)
5	1.228	0.042	-0.028	0.068	0.017	0.022	-0.08			0.236	-0.084	4.436
	(5.172)***	(0.416)	(-0.446)	(1.028)	(0.351)	(0.438)	(-0.725)			(3.49)***	(-1.527)	(4.13)
6	1.212	0.051	-0.022	0.063	0.013	0.016	-0.083	-0.378	-0.312	0.239	-0.084	4.662
	(5.144)***	(0.505)	(-0.349)	(0.955)	(0.254)	(0.318)	(-0.76)	(-1.077)	(-1.103)	(3.593)***	(-1.549)	(4.281)

Table 11: *Fama-MacBeth regression analysis for the innovations (first differences) on the value-weighted average industry volatility (INDvw), $\Delta INDvw$.* The left-hand side (test or basis assets) are excess returns of individual stocks. The right-hand side are betas of CAPM-FF3-FF5 factors and the innovations on average industry volatility (IND). I use a value weighting scheme (vw). In Panel A I control for innovations on market volatility (MKT), average firm volatility (FIRM), again with their respective weighting scheme, using exclusively the CRSP database. In Panel B I additionally control for size and value, using the merged CRSP/Compustat (CCM) database. The period for the time-series 60-month rolling regressions to estimate the βs is 07:1963–12:2015. The period for the cross-sectional regressions is 08:1968–12:2015. Shanken (1992) t-statistics which account for error-in-variables of the estimated betas are reported in parentheses. *, **, *** denote significant coefficients for the 10%, 5% and 1% significance levels, respectively. The last column reports the average coefficient of determination, R^2 and $adj - R^2$ in parenthesis, across the cross-sectional regressions.

8 Conclusion

8.1 Discussion

To the best of my knowledge, past research has produced controversial findings on the pricing of market-wide volatility and the idiosyncratic stock volatility without studying whether idiosyncratic industry volatility is priced. In the thesis, I argue that idiosyncratic industry volatility could be a priced for the cross-section of stock returns because there are investors who hold industry-concentrated portfolios. I investigate three dimensions of industry volatility, the average industry volatility as a factor and the idiosyncratic industry volatility as a factor and as a characteristic. I calculate the three dimensions of industry volatility, based on the indirect decomposition method of Campbell et al. (2001), and I decompose volatility of stock returns to market-wide, industry- and stock-level components. Then, I conduct Fama-MacBeth cross-sectional regression analyses using individual stocks as basis assets. I test the pricing of industry volatility augmenting the CAPM and Fama and French three- and five-factor baseline models with the respective factor sensitivities of the constructed volatility series.

I find support for the strands of literature that postulate a negative relationship between the stock returns and the idiosyncratic stock volatility (Ang,Hodrick, Xing, and Zhang (2006)) or the market-wide volatility (Cremers, Halling and Weinbaum (2015)). I find that the factor sensitivity of the average industry volatility could be priced for the cross-section of stock returns when I assign the stocks to 49 SIC-based industries. However, this result is not robust when I control for size and market volatility beta or consider two additional industry classifications. Furthermore, I find that the factor loadings of the idiosyncratic (individual) industry are not priced as an industry-varying risk factor for the cross-section of stock returns.

Next, I study the idiosyncratic industry volatility as characteristic. Fama-MacBeth cross-sectional regressions show that idiosyncratic industry volatility is priced as characteristic. This result is robust when I form quintile portfolios sorting the stocks on their individual industry volatility, and adapting the work of Ang et al. (2006) for the idiosyncratic stock volatility to the industry level. I perform two robustness checks, by calculating the idiosyncratic industry volatility with the indirect and direct decomposition methods. I find that the CAPM and Fama and French three- and five-factor models cannot price the spread portfolios of the quintile portfolios. The mispricing of the Fama and French three- and five-factor models is between -0.395% and -0.469% for both decomposition methods.

However, I find that the pricing of the magnitude of idiosyncratic industry volatility is sensitive to the minimum month requirement in implementing the Fama-MacBeth procedure. When I require at least 48 months instead of 24 there is no statisticaly strong relation between the magnitude of idiosyncratic industry volatility and the cross-section of stock returns.

Last, in order to examine the robustness of the results for the Fama-MacBeth cross-sectional regression analyses, I consider two different industry classifications. First, I consider a SIC-based classification of a higher level of coarseness, forming only 10 industry divisions instead of the aforementioned 49 industries. Second, I also consider a classification based on the Fixed Industry Classification (FIC) scheme of Hoberg and Philips (2010), who construct it by textually studying the activity description from the 10-K reports of each firm, forming 25 industries My results indicate that they are, in general, robust when I consider the two SIC-based classifications, but not when I consider the FIC-based classification. However, I do not examine the potential selection bias by using the FIC-based industry classification scheme. Thus, I argue that studying multiple industry classifications is important for drawing robust conclusions on industry level analyses.

8.2 Limitations and Future research

In the thesis, I only use as controls for the three dimensions of industry volatility the other volatility series calculated from the indirect decomposition method of Campbell et al., and the magnitudes of size and value for each stock. As baseline models for the Fama-MacBeth cross-sectional regressions I have only used the CAPM, and Fama-French three- and five-factor models. Hence, I do not control for the momentum factor of Carhart (1997). Hong, Lim, and Stein (2000) argue that the negative effect of momentum is more intense on declining stocks than the positive effect on rising stocks. Moreover, during early 2000 and the financial crisis of 2008-2009 the U. S. stock market experiences a decline, and subsequently a rise in all the three volatility measures, at the market-, industry- and firm-level. Hence, this could mean that at least a part of the negative assossiation of the stock returns to the idiosyncratic industry volatility could be due the momentum effect.

Huang, Liu, Rhee and Zhang (2010) have claimed that return reversal neutralises the negative relation between stock returns and stock idiosyncratic risk. Hence, if there is a confounding relationship between idiosyncratic industry volatility and idiosyncratic stock volatility as the evidence suggest in Section 6.3, controlling for return reversals could potentially neutralise the negative relation of idiosyncratic industry volatility to stock returns.

Moreover, in the thesis, I allow time-variation in the factor loadings, using sixty-month rolling time-windows. However, Harvey and Siddique (2000) claim that using the full-information maximum likelihood (FIML) estimation method with constant and not rolling betas produces results with more explanatory power, but the thesis does not use any other estimation methods but instead relies only on OLS. Hence, the thesis could also encompass other estimation methods, like FIML and the Generalised Method of Moments (GMM).

Furthermore, the literature uses portfolios as basis assets in order to deal with the error-in-variables problem, during the estimation of the betas. However, Chordia et al. (2015) propose an adjustment specifically for cross-sectional regression which have as independent variables factor loadings and characteristics, which the thesis does not use.

More importantly, the thesis does not study how the potential collinearity of the datasample, affects the results, but just conjectures on a confounding relationship between idiosyncratic stock and industry volatility. The mean “cross-sectional” betas of the volatility series are very close to zero and this fact hints that the models used in the thesis could be misspecifiedspecified, since the betas of the volatility series do not have enough variation to correctly estimate the volatility series’ risk premia. Hence, future research on the pricing of industry volatility should clearly address this issue.

Furthermore, the thesis does not examine separate industries, but the whole cross-section of stock returns. Since literature has shown that the returns are cross-predictable in economically-related industries (Menzly and Ozbas (2010)) and that volatility schocks could have a causal relationship to the volatility of other industries (Wang (2010)) it would be interesting to examine whether there are particular patterns in the idiosyncratic industry volatilities among economically-related industries.

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