UNIVERSITY OF LJUBLJANA
FACULTY OF ECONOMICS

MASTER’S THESIS

AN EMPIRICAL INVESTIGATION OF COMMON FACTORS IN IDIOSYNCRATIC VOLATILITY

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AUTHORSHIP STATEMENT

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INTRODUCTION

One of the most prevalent financial observations is a positive association between expected return and risk. Investments would lose their attraction if the expected rate of return is insufficient to compensate the investor for bearing related risk. Aggregate market risk has been considered as the main risk that should be compensated. Treynor (1962), Sharpe (1964) and Lintner (1965) developed the capital asset pricing model (hereinafter: CAPM) to determine an appropriate level of return required for an asset. The model separates risk-return relationship into a systematic and an idiosyncratic part, and it assumes that only the systematic part of an asset's return should be priced. The idiosyncratic risk, on the other hand, should not be included in an asset's price because it can be eliminated by diversification. One major pitfall of the CAPM model is that it results in that rational market participants will only hold the market portfolio and risk-free assets. Most investors, however, may hold under-diversified portfolio. Therefore, the assumption that all investors will optimize their portfolios is violated.

Subsequent research has shown that CAPM fails to explain market anomalies such as the size and value effect, namely, market return cannot adequately account for the systematic risk of an asset. Following the development of arbitrage pricing theory (Ross, 1976) (hereinafter: APT), researchers developed multiple-factor models to explain the pricing mechanism. One of the most well-known and accepted models is the Fama and French three-factor model (Fama & French, 1993). In addition to market risk, size and growth risk are also taken into account. Subsequently, their model was augmented by adding an additional momentum factor (Cahart, 1997). Nevertheless, these models still imply that only the systematic risk captured by common factors should be priced. Some researchers argue that these factor models could not accurately reflect the reality of the market. Most importantly, investors are unlikely to hold well-diversified portfolios for various reasons. Firstly, investors may not be able to purchase fully-diversified portfolios due to wealth limitation. Secondly, transaction costs may arise from frequent holdings and rebalancing stocks in portfolios. Thirdly, investors take large stakes in certain stocks in order to exploit arbitrage opportunities. Numerous empirical studies document anomalies that investors prefer a certain flavor of stocks. For example, a person is more prone to invest in familiar companies around her local geographical area instead of adapting portfolio theory's suggestion to diversify (Huberman, 2001). Moreover, during the time of crisis, the diversification benefit can diminish away. Therefore, both systemic and idiosyncratic risk exist in most investors' portfolios. Idiosyncratic volatility is used as a proxy for idiosyncratic risk. Consequently, the link between idiosyncratic volatility and the average rate of return concerns a substantial share of investors.

Recently, an increasing body of research shed light on the importance of idiosyncratic risk. Campbell, Lettau, Malkiel and Xu (2001) documented an increasing trend in idiosyncratic volatility and proposed several likely causes, such as the alternation in company governance and the institutionalization of equity proprietorship. In addition, they also showed that idiosyncratic volatility accounts for the largest piece of total volatility. Thus, idiosyncratic risk would be the greatest risk for investors who hold an under-diversified portfolio. On the contrary, Brandt, Brav, Graham and Kumar (2010) indicated a decreasing idiosyncratic volatility pattern from late 90's and concluded that the earlier rise in idiosyncratic volatility between 1962 and 1997 is not a time trend, but induced by the speculative trading from retail investors. Subsequent literatures were dedicated to the study of the relationship between idiosyncratic risk and stock returns.

In particular, Merton (1987) proposed an extension to the CAPM model where idiosyncratic risk is priced, and idiosyncratic risk should be positively correlated to the expected return. Merton's hypothesis states that due to incomplete information on stock markets, investors tend to hold only those stocks which they are familiar with and demand compensation for bearing idiosyncratic risk. On the contrary, a recent research by Ang, Hodrick, Xing and Zhang (2006) showed that stocks, which are associated with high idiosyncratic risk, constantly generate lower returns. In particular, they found that the stock return spread between the highest idiosyncratic volatility quintile and the lowest idiosyncratic volatility quintile is approximately -1% per month. Furthermore, they proved that this anomaly cannot be explained by either size, book-to-market, leverage, liquidity, volume, turnover, bid-ask spreads, coskewness or dispersion in analysts' forecasts. Besides, the phenomenon persists through several subsamples in different time periods. In their follow-up study, they explored this relationship between idiosyncratic risk and stock returns using a world-wide data set, and proved that this relation is not only limited to the US stock market (Ang, Hodrick, Xing, & Zhang, 2009). In other words, investors are not compensated by undertaking additional idiosyncratic risk. Their finding clearly contradicts the traditional financial theories such as stocks with higher idiosyncratic risk should yield higher expected return because investors are unable to diversify the individual specific risk (Merton, 1987) and thus, can be considered as an empirical puzzle.

Subsequently, their finding faced extensive criticism. Fu (2009) challenged Ang, Hodrick, Xing and Zheng's findings by arguing that idiosyncratic volatility is a time-varying process. He showed that the approach of estimating idiosyncratic volatility used by Ang et al. (2006) is not a valid proxy for the real expected value: Ang et al. (2006) estimated idiosyncratic volatility by calculating the standard deviation of daily residuals in each given month. Fu argued that idiosyncratic volatilities are time-varying and auto-correlated, monthly average volatility cannot capture this property sufficiently, thus is not a good proxy for the expected value. Therefore, in Fu's argument, Ang, Hodrick, Xing and Zheng's (2006) finding does not reveal the true relationship between idiosyncratic volatility and expected return. In contrast, Fu (2009) used EGARCH models in order to incorporate the auto-correlation of idiosyncratic volatility. He found a positive correlation of high idiosyncratic risk and high expected returns instead, and confirmed his finding to be both statistically and economically significant and robust to different empirical specification. He ascribed the puzzling result from Ang et al. (2006) partly to their inclusion of a subset of firms with small capitalization and high idiosyncratic risks. These small stocks with high idiosyncratic risk has been the main driver of the negative correlation of idiosyncratic volatility and subsequent monthly returns. This debate suggests that the estimation methodology of idiosyncratic risk, the treatment of outliers and the inclusion of illiquid stocks are critical for statistical inference.

Several researchers criticized Ang et al. for reasons other than the estimation methodology. For example, Bali and Cakici (2008) confirmed that different estimation methods or frequencies can twist the manifestation of the return – idiosyncratic volatility relationship. Beyond that, they indicated that controlling for size, price, liquidity and sample selection have a crucial influence on the outcome. Consequently, they found that idiosyncratic volatility is not robustly correlated with expected returns. Cao and Xu (2010) decomposed idiosyncratic volatility into long-run and short-run terms and found a negative correlation between idiosyncratic volatility and expected return in the short-run and positive correlation in the long-run. Both Malkiel, Xu (2004) and Nath (2012) suggested the relationship is non-linear, but parabolic and dynamic essentially. Despite of contradictory views, it is commonly agreed that, first, the idiosyncratic risk – expected return relation is sensitive to the choice of estimation method used, second, the idiosyncratic risk is not fully diversified and investors should be compensated for bearing it (investors should pay attention to the level of idiosyncratic risk in their portfolio and watch the possible change under different market turbulence).

Despite numerous studies that focused on idiosyncratic volatility, there have been only a few published papers that investigate the dynamics of common components of firm-level idiosyncratic volatility. Duarte, Kamara, Siegel and Sun (2014) studied the common component of idiosyncratic volatility calculated from the Fama-French model and showed that the idiosyncratic volatility puzzle is due to unaccounted systemic risk. They used the method of asymptotic principal components method to decompose monthly idiosyncratic volatilities into a matrix of common components and another matrix of unexplained variation in volatilities. By applying a single common component of idiosyncratic volatility, it explains 32% of individual variation and five common components account for nearly 50% of variation. They formed Predicted Idiosyncratic Volatility (hereinafter: PIV) as a new risk factor from the common components that have the highest explanatory power of volatilities. Furthermore, they found that this risk factor is highly correlated with business cycle proxies and recommended an addition of a new risk factor into the Fama-French framework.

The work from Herskovic, Kelly, Lustig and Nieuwerburgh (2014) found that idiosyncratic volatility is correlated with households' labor income risk, and suggested common idiosyncratic volatility as a priced factor. Most importantly, they documented that there is a relatively small difference between stocks' total volatility and idiosyncratic volatility. Moreover, there exists strong co-movement of individual return volatilities, aggregate stock volatilities of either different size groups or industry groups share a general pattern of movement. They derived the common factor of firm-level idiosyncratic volatilities by estimating annual idiosyncratic volatility based on CAPM, Fama-French three-factor and five principal components model respectively, which is very similar to the method implemented by Duarte et al. (2014). The common component is acquired by using the equal-weighted averaging, which is, in essence, approximately equal to the first principal component from the principal component analysis. Interestingly, the conclusion of the analysis does not alter significantly by implementing different asset pricing models. This result coincides with the finding of Nath (2012), who shows that idiosyncratic volatility – return relationship is not sensitive to the choice of CAPM one-factor or Fama-French three-factor models, but instead is sensitive to the choice of estimation method of volatility and data frequency used.

Despite the similarities in methodology used by Duarte et al. (2014) and Herskovic et al. (2014): they implemented identical asset pricing model and both used the first principal component as the proxy for the common factor. However, the same choice of common factors was subject to different interpretations. Duarte et al. (2014) only suggested a common component of idiosyncratic volatilities (PIV) as an omitted risk factor from the Fama-French model, whereas Herskovic et al. (2014) provided additional insight by validating that the common variation in idiosyncratic volatility cannot be explained by co-movement among factor model residuals (omitted common factors). Nevertheless, Herskovic et al. (2014) still found the common idiosyncratic volatility as a valuable priced variable. Moreover, the expected return is found to be negatively correlated with its exposure to common idiosyncratic volatility. Finally, they proposed a theoretical model that predicts a negative relationship of CIV and risk sharing and a positive association of CIV and individual marginal utility. One potential pitfall of these two papers is that they didn't take the autocorrelation property of volatilities into account, instead, used monthly or yearly standard deviations of model residuals as an idiosyncratic volatility measure. The consequence might be, as mentioned above: the choice of estimation method and frequency can lead to different risk – return relationship.

Several studies focused also on the aggregate volatility. Namely, the definition of aggregate volatility is very similar to the common idiosyncratic volatility. Bekaert, Hodrick and Zhang (2012) conducted an international study of aggregate idiosyncratic volatility in stock markets. They first confirmed that idiosyncratic volatility is a stationary and mean-reverting process and there exists no apparent ascendant pattern in idiosyncratic volatilities worldwide. Moreover, they showed that three groups of variables determine aggregate idiosyncratic volatility: index composition variables; corporate characteristics, which affect cash flow variability; and business cycle indicators. Few cash flow variables such as average book-to-market value, and several macroeconomic indicators and market-level volatilities are found to have the highest explanatory power. Moreover, higher aggregate idiosyncratic volatility is found in the times of financial crises and bear markets, which is consistent with the view that a common component of idiosyncratic volatility as a systematic risk factor. In another study, Chen and Petkova (2012) attempted to explain aggregate market volatility by average stock return variance and average stock return correlation. Stocks with high idiosyncratic volatility are found to have higher loading on the innovation in average stock return variance. Accordingly, the average variance was ascribed as the missing factor to explain the idiosyncratic volatility puzzle.

A related study investigated the relationship between idiosyncratic volatility and liquidity, and showed that low idiosyncratic volatility stocks intertwine with high liquidity (Spiegel & Wang, 2005). However, idiosyncratic volatility is found to have an important role in determining the expected return when controlling for other effects which were included in the model specification. Lee and Liu (2011) decomposed idiosyncratic volatility into one part caused by random noise and another part caused by firms' fundamental health information. Schneider (2011) concluded that the increase in idiosyncratic volatility during the crisis cannot be fully explained by a chosen sample of firm fundamentals. Connor, Korajczyk and Linton (2006) modeled the total volatility with macroeconomics factor, common and idiosyncratic firm-specific variables. However, they did not investigate the implication on asset pricing. Dennis and Strickland (2004) indicated a positive relationship between idiosyncratic risk and innovations in institutional ownership.

The idea of industry-specific common factor in idiosyncratic volatility is also interesting, although thus far no published paper studies this issue. Herskovic et al. (2014) showed that idiosyncratic volatilities have very close common trends among industry groups, they share a high level of correlation. Mazzucato & Tancioni (2008) studied the relationship between innovation and idiosyncratic risk, they found an inconclusive pattern by using industry-level data. However, by using firm-specific data, firms with the highest R&D intensity is proven to be most volatile in their returns. Luis & Timmermann (2003) documented that common components from different industries affect returns from industries in a different manner, such as the oil shock and information technology bubble. Therefore, an initiative idea could be investigation whether there is significant difference in idiosyncratic volatility by industrial specification. In another word, whether industrial diversification can help an investor to lower the aggregate volatility of her portfolio. If a high-level of correlation is found in cross-sectional industrial idiosyncratic volatilities, it would be worthless to diversify the portfolio by selecting different industrial components, thus it would be meaningless to study the industry-specific common factors. On the other hand, if the industry volatilities show a distinctive pattern, it suggests that idiosyncratic volatility may have different underlying common factors by industry.

After reviewing several literatures, the following content of this introduction provides a brief theoretical motivation of this thesis:

A rich body of literature has been dedicated to the investigation of idiosyncratic volatility. Heated debate has arisen over its impact on the expected stock return and the underlying determinants. As already mentioned above, several studies showed that high idiosyncratic volatility coincides with a low abnormal return, which is in stark contrast to conventional theory, which argues that investors should be rewarded for taking a higher idiosyncratic risk. Despite controversy, those studies still come up with a consensus that idiosyncratic volatility is relevant for major market participants. Due to various constraints, idiosyncratic risk cannot be fully diversified for either individual or institutional investors.

In this thesis I shall 1) investigate the level of common variation in firm-level idiosyncratic volatility, 2) explore the characteristics of common components in idiosyncratic volatility including its effect on the expected stock return, 3) determine the underlying driver for time-series dynamics of idiosyncratic volatility. Prior to the study of commonality in idiosyncratic volatilities, this thesis will firstly investigate the contemporaneous relationship between idiosyncratic volatility and expect return. This will help me in determining the specific pattern of idiosyncratic volatility in the sample used, and pave the way for further study of the effect of common idiosyncratic volatility on cross-sectional idiosyncratic volatility.

The discovery of strong co-movement in firm-level idiosyncratic volatility by Herskovic et al. (2014) is highly noteworthy. Traditional asset pricing models rely on diversification of idiosyncratic risk. If certain components of individual idiosyncratic volatility cannot be diversified away, then they should be included in the pricing model. A replication of cross-sectional investigation of idiosyncratic volatilities by Herskovic et al. (2014) will be firstly implemented in order to determine the level of co-movement in idiosyncratic volatility. In addition to cross-sectional comparisons in certain groups, the average level of correlation within individual idiosyncratic volatility will also be examined to provide further evidence. This section will be the pith of the thesis and a building block for further examinations.

The second main focus is to investigate the time-series behavior of common idiosyncratic volatility. There has not been a huge debate on the choice of method for extracting the common factors. Duarte et al. (2014) used the asymptotic principal component analysis to decompose volatility, while the majority of researchers used equally-weighted averaging to compute aggregate idiosyncratic volatility. This is important not only for the purpose of exploring the pattern of overall idiosyncratic volatility, but also for determining the effect of common components on individual idiosyncratic volatility behavior. The contemporaneous relationship between expected return and common idiosyncratic volatility will be further studied. This will help to explain the impact of residual idiosyncratic volatility of stock returns and indicate whether the common idiosyncratic volatility should be treated as a priced factor.

In addition, the determinant of common idiosyncratic volatility will be sought in order to assist in understanding the dynamics of idiosyncratic volatility. Several papers pointed out a strong correlation between business cycle and aggregate idiosyncratic volatility. This phenomenon has a valuable implication: If the common idiosyncratic volatility has a significant impact on the expected return and meanwhile it is highly correlated with macroeconomic state variables, then one can infer that the common idiosyncratic volatility represents systemic risk. Therefore, the relationship between common idiosyncratic risk and the impact of the business cycle will be verified by testing several macroeconomic indicators.

Finally, this thesis will be dedicated to the investigation of idiosyncratic risk of the U.S. stock market during the recent times. The sample used in thesis spans from June 1994 to June 2014. The use of data can provides a direct comparison with related researches. However, relatively short time span used in this thesis might alter the results comparably. Since most of studies chose a longer time horizon. Nevertheless, this thesis is expected to evaluate the impact of common idiosyncratic volatility on asset returns and provide insight into investigating the underlying factors driving its dynamics in this thesis.

The rest of this thesis is organized as follows:

Section 1 presents the theoretical background and econometric methodology used. Thesis is built on the foundation of arbitrage pricing theory and Fama-French three-factor model. In this section, the estimation method for computing idiosyncratic volatility and the test for choosing an appropriate estimation technique are presented. Moreover, a brief overview of Fama-Macbeth cross-sectional regression establishes the groundwork for assessing an augmented asset pricing test at the end of the thesis.

Section 2 provides the empirical results based on the mentioned empirical methodologies. Summary statistics of the data and computed idiosyncratic volatility are presented. Specifically, section 2.4 investigates the impact of residual idiosyncratic volatilities on stock returns. Subsequently, section 2.5 is focused on the evaluation of commonality in cross-sectional idiosyncratic volatilities.

Section 3 extracts the common factor of idiosyncratic volatility and investigates its ramifications. Firstly, the general characteristics of common idiosyncratic volatility are studied. Furthermore, the impact of common idiosyncratic volatility of stock returns is investigated. The robustness of the impact is also investigated by controlling for several external effects. Subsequently, several regressions are carried out in order to explore the underlying dynamics of common idiosyncratic volatility. At the end of this section, common idiosyncratic volatility is investigated as a pricing factor using Fama-Macbeth method.

1 THEORETICAL BACKGROUND AND METHODOLOGY

1.1 Arbitrage Pricing Theory and Fama and French Three-Factor Model

The pith of modern asset pricing models is the quantification of the tradeoff between risk and return. The kernel of investment choices is essentially the balance of risk and return relationship. The Capital Asset Pricing Model introduced by Sharpe (1964) and Lintner (1965) is the first, and most widely used asset pricing model. CAPM argues that rational investors should always decide between a risk-free investment and the market portfolio.

The sensitivity to excess market return, which is calculated as beta, tells the amount of compensation required by investors to accept additional risk. However, despite simplicity and theoretical reasonableness, CAPM suffers from a number of criticisms. Notably, a set of considerably restrictive assumptions make CAPM not viable in reality.

1.1.1 Arbitrage Pricing Theory

The Arbitrage Pricing Theory was introduced by Ross (1976) as an alternative model to classical CAPM. APT can be used more generally than CAPM as it adopts a greater number of risk factors as well as more lenient enforcement of assumptions. Moreover, typically APT has a greater explanatory power than CAPM. Ross's APT relies on three major assumptions (Ross, 1976):

i) Security returns can be described by a factor model.

ii) Idiosyncratic risk can be diversified away by a sufficient number of securities.

iii) Efficient security markets do not allow for persisting arbitrage opportunities.

The APT model may be viewed as an application of the law of one price, which states that two economically equivalent assets should have the same price in every market. Arbitrageurs will ensure every arising arbitrage opportunity to be transient. While an arbitrage opportunity occurs whenever a zero investment portfolio can earn risk-free profits (Bodie, 2009). A multifactor APT model for individual asset returns has the following general form (Munk, 2008):

$$R_i = E[R_i] + \sum_{k=1}^{K} \beta_{ik} x_k + \varepsilon_i; \quad E[x_k]=0,\ E[\varepsilon_i]=0,\ Cov[\varepsilon_i, x_k]=0 \qquad (1)$$

where x_k are *factors*, the β_{ik} are the factor loadings and the ε_i are residuals. $E[R_i]$, also denoted as alpha in some literature, stands for the constant level of return for the asset ***i***. Equation (1) states that deviation of actual return from the expected return for asset ***i*** can be split into systematic risk factors, $\sum_{k=1}^{K} \beta_{ik} x_k$, and idiosyncratic component ε_i. The pivotal notion of APT is that in a well-functioning security market, there should be enough securities to diversify away idiosyncratic risk completely. Therefore, investors will not be compensated for holding additional idiosyncratic risk.

Ross (1976) sets up a portfolio with a weighting vector $\boldsymbol{w} = (w_1, \ldots, w_I)^T$. Weights sum up to one. Subsequently, the portfolio return has the form (Munk, 2008):

$$\boldsymbol{R^w}=\boldsymbol{w^T R}=\sum_{i=1}^{I} w_i E[R_i] + \sum_{i=1}^{I} w_i \beta_{i1} x_1 + \ldots + \sum_{i=1}^{I} w_i \beta_{iK} x_K + \sum_{i=1}^{I} w_i \varepsilon_i \qquad (2)$$

If there exists a set of $\boldsymbol{w}$ so that the portfolio is a risk-free zero-investment portfolio. Thereby, one can expect that:

$$\boldsymbol{R^w}=\sum_{i=1}^{I} w_i E[R_i] = 0 \qquad (3)$$

Since the portfolio has zero net value, it also holds that $\sum_{i=1}^{I} w_i \beta_{ik} = 0$ for $k = 1, \ldots, K$. By imposing that $\sum_{i=1}^{I} w_i \varepsilon_i = 0$, a portfolio has no exposure to idiosyncratic risks. Equilibrium in (3) has to be true to satisfy arbitrage-free condition. If this were strictly true, subsequently there exists a constant α and factor risk premia η such that:

$$E[R_i]=\alpha+\sum_{k=1}^{K} \beta_{iK} \eta_k \qquad (4)$$

Accordingly, the expected return on an individual asset is a linear combination of a constant and a set of pricing factors. Analogously it can be shown that all assets have an expected return described in a K-dimensional hyperplane with $\alpha = R_f$ and $\eta_k = \bar{R}_k - R_f$ that (Elton & Gruber, 2014):

$$E[R_i]=R_f+\beta_{i1}\left(\bar{R}_1-R_f\right)+\ldots+\beta_{iK}\left(\bar{R}_K-R_f\right) \qquad (5)$$

where R_f can be interpreted as risk-free rate and $\left(\bar{R}_k - R_f\right)$ terms are risk premia demanded for each class of risk factors.

However, APT does not provide any guidance regarding the choice of relevant pricing factors. Yet two principles assist in the selection of advisable factors (Bodie, 2009). First, the set of explanatory factors should be limited to a narrow range. Second, investors should demand sufficient risk premiums on chosen factors. In general, APT factors are classified into three categories. Namely, macroeconomic factors such as GNP growth and inflation; fundamental factors such as P/E, size proxy for factor loadings; and statistical factors estimated by statistical techniques.

One of the most often used estimation methods for APT is the two-stage Fama-Macbeth regression, where first stage involves estimation of a set of time-series regressions for individual assets, and in the second stage estimation of cross-sectional regression of the returns estimated in the first stage.

The empirical tests examine whether APT explains the cross-sectional differences in asset returns. Accordingly equation (4) will be tested with corresponding null hypothesis (H_0) that all the β_{iK} equals zero, the alternative hypothesis (H_a) would be that at least one of factor loadings is non-zero (Chen N. , 1983). Fama and MacBeth (1973) used t-test to identify the significance of the risk premium.

1.1.2 Fama and French Three-Factor Model

A great fraction of literature on factor models is built on empirical research. The chosen factors are variables, which tend to predict average returns fairly well based on historical evidence. The most well-known model is a three-factor model based on firm characteristics (Fama & French, 1993). Authors find that cross section of average returns has a negative relation with firm size (based on market capitalization) and positive relation with the value (book-to-market ratio). Yet it is tough to incorporate these variables into the model. Usually at least monthly observations are required for time-series estimation of a factor model, however, firm fundamentals such as book value of equity, are merely reported at most quarterly. Fama and French create factor mimicking portfolios that convert firm fundamentals into more frequent and flexible series. Subsequently the factor construction follows a two-step method (Elton & Gruber, 2014):

Step 1: Two size groups are defined by separating all stocks listed on NYSE, AMEX and NASDAQ by their market capitalization. Big stocks are above the median size of a stock on the NYSE and small stocks are below. Moreover, firms are divided into three groups based on their book-to-market ratio. The breakpoints are set to 30% (growth), 50% (neutral) and 70% (value) quantiles. Consequently this two-way classification forms six portfolios being rebalanced annually.

Step 2: The portfolios are broken into six groups in order to orthogonalize value and size effects. Subsequently the size variable reflects the excess return of small caps over big caps and capturing firm size is defined as Small Minus Big (SMB):

$$\begin{aligned} SMB = 1/3\,(SmallValue + SmallNeutral + SmallGrowth) \\ -1/3\,(BigValue + BigNeutral + BigGrowth) \end{aligned} \tag{6}$$

where *SmallValue* denotes the average return of the portfolio contains small caps and growth firms for instance. Similarly, the value variable reflects the excess return of firms with high book-to-market values over firms with low book-to-market values and is defined as High Minus Low (HML):

$$HML = 1/2\,(SmallValue+BigValue)-1/2\,(SmallGrowth+BigGrowth) \qquad (7)$$

Lastly, the third variable is the value-weighted excess return on the market. Thus, the expected return on asset *i* is:

$$E(R_i)-R_f = b_i[E(R_m)-R_f]+s_iE(SMB)+h_iE(HML) \qquad (8)$$

Notably Fama and French build the model without support of financial theory: While SMB and HML are not themselves obvious candidate for relevant risk factors, the argument is that these variables may proxy for yet-unknown more fundamental variables (Bodie, 2009).

However in the most recent work, Fama and French have released their new finding on the factor model (Fama & French, 2015). The new model sheds light on additional two factors, namely profitability factor (RMW) and investment factor (CMA). The rationale behind these two is that companies with higher future earnings or with conservative investment activities will yields higher returns. Surprisingly, by incorporating new factors, the value factor (HML) becomes completely redundant and can be replaced by the other four factors.

1.2 Estimation Method

In a general factor model, idiosyncratic volatility is the part of total volatility which cannot be observed directly. The factor model has the following form:

$$R_{it}=E[R_i]+\sum_{k=1}^{K}\beta_{ik}x_{kt}+\varepsilon_{it}; \qquad (9)$$

where, by construction, x_{kt} and ε_{it} are orthogonal, $\text{Cov}(x_{kt},\varepsilon_{it})=0$. Equally, x_{kt} are set to be mutually independent. Accordingly, one can decompose the variance of individual return into two major components:

$$Var(R_{it})=\sum_{k=1}^{K}\beta_{ik}^2 Var(x_{kt})+Var(\varepsilon_{it}) \qquad (10)$$

By taking the square root of $Var(\varepsilon_{it})$ is the idiosyncratic volatility of asset i.

Replicating (Ang, Hodrick, Xing, & Zhang, 2006) and (Duarte, Kamara, Siegel, & Sun, 2014), a standard time-series regression can be implemented using daily excess returns on the Fama-French three factors:

$$R_{it}\text{-}R_{f,t}= \alpha_i+\beta_i^{MKT}MKT_t+\beta_i^{SMB}SMB_t+\beta_i^{HML}HML_t+\varepsilon_{it} \quad (11)$$

Where R_{it} indicates return of stock i at time t, $R_{f,t}$ indicates the corresponding risk-free rate. MKT_t, SMB_t and HML_t are the Fama-French factors. Next the idiosyncratic volatility of stock i for month m is defined as average squared residual from (11) over the number of trading days within month m, $T_{i,m}$:

$$IV_{i,m}=\sqrt{\frac{1}{T_{i,m}}\sum_{t=1}^{T_{i,m}}\varepsilon_{i,t}^2} \quad (12)$$

1.3 Detection of Fixed Effects and Fixed-Effects Model

The pooled least squares regression yields a constant level over time, this is however a strong assumption. In contrast, factor loadings might vary with time. Monthly regression (Duarte, Kamara, Siegel, & Sun, 2014) or rolling regression is not adapted in this thesis in order to avoid the complication arising from recursive computing. As an alternative, by including binary time variables, one can capture the potential time-varying relationship between average excess returns and factors.

Therefore, one feasible remedy is to extend (11) to include indicator variables for different time periods and estimate the model using the least squares dummy variable (LSDV) method. Accordingly, the augmented model with time effects is (Greene, 2003):

$$R_{it}\text{-}R_{f,t}= \alpha_i+\beta_i^{MKT}MKT_t+\beta_i^{SMB}SMB_t+\beta_i^{HML}HML_t+\gamma_k+\varepsilon_{it} \quad (13)$$

Where γ_k measures the fixed effect of time k. The model also imposes a restriction: $\sum_k \gamma_k = 0$. k is a number of a specific year month; the LSDV model requires inclusion of additional K-1 binary indicator variables for γ_k. Finally, the LSDV model can be estimated using the ordinary least squares method.

To investigate whether fixed effects are present in Fama-French three-factor model (hereinafter: FF-3 model), one can use F test to examine the significance of time and group effects (Greene, 2003) :

$$F(n\text{-}1,nT\text{-}n\text{-}K)=\frac{(R_{LSDV}^2\text{-}R_{Pooled}^2)/(n\text{-}1)}{(1\text{-}R_{LSDV}^2)/(nT\text{-}n\text{-}K)} \tag{14}$$

Where R_{LSDV}^2 is R-squared of LSDV model and R_{LSDV}^2 is the corresponding term of restricted model without binary variables. Large value of F-test rejects the null hypothesis that all the fixed effects coefficients equal zero.

1.4 Fama-Macbeth Two-Step Procedure

There have been several statistical methods to evaluate an asset-pricing model, Fama-Macbeth two-step procedure is one prevailing technique to measure the risk-factor premium for pricing models. In the first step, a time-series regression is performed to obtain assets' loadings on each factor. In the next step, a cross-sectional regression of all asset returns is implemented against all the estimated loadings in order to compute the risk premium (Fama & MacBeth, 1973). Cochrane shows that this technique is essentially equal to a pooled time-series and cross-sectional ordinary least square estimation. Specifically, individual betas are estimated in the time-series regression firstly. Afterward, cross-sectional regressions are implemented at each time period (Cochrane, 2005).

$$R_{it}^e=\boldsymbol{\beta}_i'\boldsymbol{\lambda}_t+\alpha_{it},\ \ i=1,2,\ldots N \text{ for each } t$$

where $\boldsymbol{\lambda}_t$ is the vector of a set of risk factors at time t, and $\boldsymbol{\beta}_i$ is the corresponding coefficient vector. In this thesis, as a replication of Ang et al. (2006), two-sort portfolios according to stock's size and value is firstly used to examine the asset pricing implication. Further, one-sort portfolios based on industry segmentation is further used to verify the result. Consequently, the average values of the cross-sectional estimates are taken as risk premiums for risk factors.

$$\hat{\lambda}=\frac{1}{T}\sum_{t=1}^{T}\hat{\lambda}_t\,;\ \hat{\alpha}_i=\frac{1}{T}\sum_{t=1}^{T}\hat{\alpha}_{it}$$

In essence, the intuition of implementing Fama-Macbeth procedure is to evaluate the explanatory power of several factors behind stock returns. Each portfolio's exposure to the factors are firstly estimated. Further portfolio's return is regressed on the factor exposure and the average coefficients determine the priced premium for every increasing unit in the factor exposure. (Fama & MacBeth, 1973)

2 EMPIRICAL FRAMEWORK

2.1 Data Description

US stock market data are obtained from Bloomberg database from June 1994 to June 2014. The basic data acquired from Bloomberg are daily stock returns with dividends adjusted for common equities listed on all the sections of New York Stock Exchange (NYSE) and National Association of Securities Dealers Automated Quotations (NASDAQ) Stock Market. Both daily and monthly returns can be calculated from daily data. Independent variables of FF-3 model are obtained directly from Kenneth French's data library. They are formed using all NYSE, AMEX, and NASDAQ stocks, American Stock Exchange (AMEX) data was acquired by NYSE in 2008 with a new name NYSE MKT. Thus there is a consistency between the data from Bloomberg database and French's data library. Moreover, 1 month US Treasury Bill rate is used as a proxy for the risk-free rate of return. In addition to stock and factor data, this study also employs ten industry classifications, market capitalization, market capitalization to book value and historical volume of each stock, which were acquired from Bloomberg database.

Following AHXZ (2006), in order to weaken the impact of infrequent trading on volatility estimation, it is required that stocks included in the sample have at least 15 trading days for each monthly idiosyncratic volatility estimated. Besides, extreme values which are above the 99.9% quantile of stock returns and below 0.1% quantile are removed.

Table 1 presents the summary statistics of the final sample through the sample period. The number of stocks nearly tripled during 20 years. Meantime, the average size increased fourfold. Table 2 contains the summary statistics for key variables concerned with FF-3 model.

2.2 Estimation of Idiosyncratic Volatility

Given the firm-by-firm regression of FF-3 model in (11) or augmented regression with additional time variable in (13), one can calculate the individual monthly idiosyncratic return volatility $IV_{i,m}$ as the square root of the average squared daily disturbance from (12). Table 3 reports a direct comparison between the FF-3 time series estimation and the augmented estimation which includes binary time variables. The average loadings on FF-3 factors, average intercept value and average R-squared are included in the table.

Correspondingly, one finds that the inclusion of time effects has no major influence on FF-3 factor loadings or the goodness of fit. The average loadings on FF-3 factors are nearly identical on two estimations. The improvement in goodness of fit is bared improved with the inclusion of time effects.

Table 1: Summary Statistics for US stocks in NYSE, AMEX and NASDAQ from 1994 to 2014

Year	Number of Stocks	Return (in %)	Size	MV/BV
1994	1165	0.036	2076	2.738
1995	1261	0.141	2405	2.640
1996	1360	0.095	2888	14.159
1997	1461	0.124	3807	3.895
1998	1538	0.005	4780	1.935
1999	1636	0.048	5798	-1.276
2000	1714	-0.025	6663	5.455
2001	1758	0.055	5699	3.093
2002	1798	-0.038	4879	-0.057
2003	1835	0.199	4809	4.025
2004	1899	0.090	5623	2.495
2005	2000	0.046	5941	2.598
2006	2075	0.085	6332	3.967
2007	2189	0.021	6908	21.787
2008	2232	-0.152	5894	0.524
2009	2262	0.127	4536	3.938
2010	2347	0.116	5430	-2.042
2011	2419	-0.009	5940	2.249
2012	2513	0.073	6168	1.254
2013	2648	0.151	7165	0.469
2014	2708	0.010	7887	4.033

Note: This table reports the number of stocks, average daily return (in percentage), average size and average market capitalization to book value ratio over the sample period.

Source: Bloomberg (2014)

Table 2: Summary Statistics of Key Variables

Variables	Mean	Std.Dev	Max	Min	Skewness	Kurtosis
Return	0.058	3.116	39.130	-38.000	0.374	11.478
MktRF	0.030	1.192	11.350	-8.950	-0.211	8.942
SMB	0.009	0.574	4.300	-4.620	-0.189	6.336
HML	0.013	0.594	3.950	-4.910	0.121	8.754
Size	5580.058	21890.550	753331.000	0.000	9.980	142.581
MV/BV	3.555	659.721	389911.500	-80800.600	421.791	211115.100
N	455946					

Note: This table reports equally-weighted average, standard deviation and other descriptive statistics for key variables of interest. MktRF is the excess return on the market portfolio, SMB is the excess return for small vs. large caps size factor and HML is the excess return for the value factor. The values for Return, MktRF, SMB and HML are reported in percentages

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

Furthermore, the average value of intercept from augmented regression is even higher than the one from original regression. By using the F-test on the pooled panel data regression, the hypothesis of fixed time effects equaling zero cannot be rejected. Therefore, the original time-series regression without time effects is used for estimation. Consequently, individual monthly idiosyncratic volatility will be estimated by adopting equation (11) and (12) for the following analyses.

Table 3: Regression of FF-3 Model

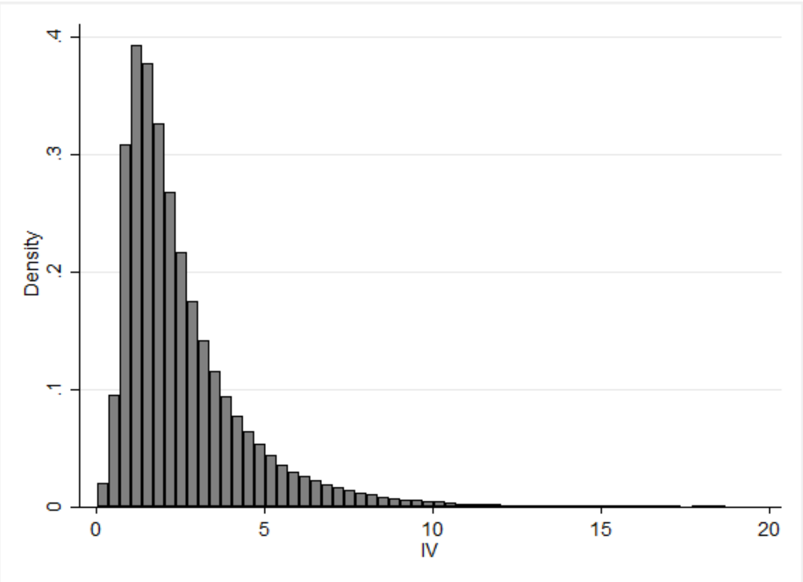
	I **Return-Rf**	**II** **Return-Rf**
MktRF	0.939	0.939
SMB	0.610	0.609
HML	0.298	0.297
Constant	0.034	0.123
Time Effects	No	Yes
adj. R^2	0.222	0.227

Note: This table reports the average value of main factor loadings by using firm level regressions and augmented regressions with binary time variables. Time effects are omitted in Column I, whereas included in Column II. The average value of adjusted R-squared is documented in the last row. Estimated coefficients regards time effects are omitted in the table.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

2.3 Descriptive Statistics of Idiosyncratic Volatility

Figure 1: Distribution of Historical Idiosyncratic Volatility



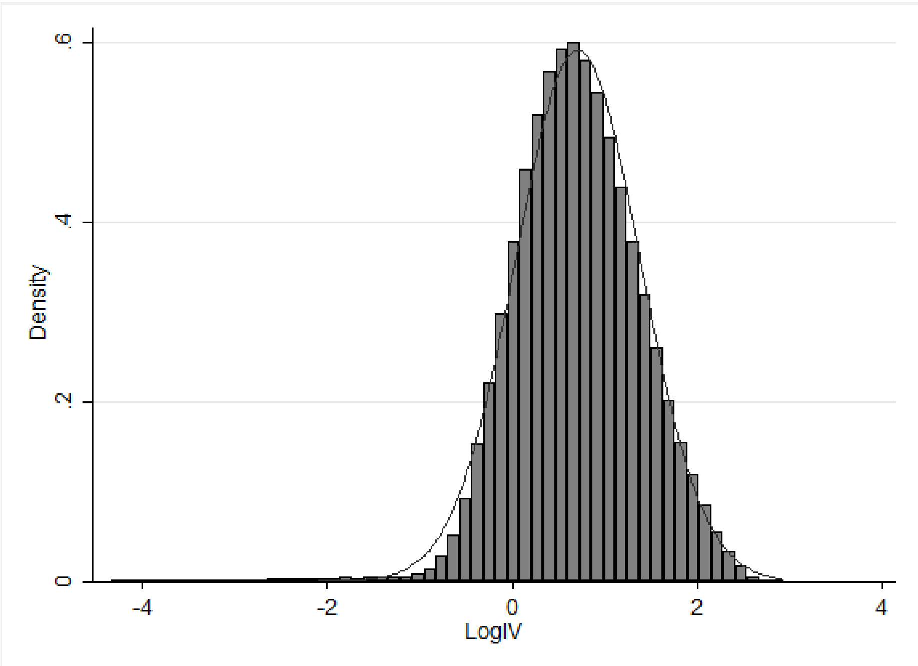
Note: This figure plots the histogram of empirical individual monthly idiosyncratic volatility from FF-3 model. The complete sample period from Jun. 2004 to Jun. 2014 is used

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

Figure 1 plots the distribution of firm-specific idiosyncratic volatility. Interestingly the shape of this histogram resembles a log-normal distribution. Therefore, one can calculate the logarithm of idiosyncratic volatility to verify this intuition. Correspondingly, Table 4 presents summary statistics of idiosyncratic volatility and its logarithm transformation. The logarithm of idiosyncratic volatility has the skewness of -0.259 and the kurtosis of 4.404, which are still in difference with the values of a normal distribution.

Furthermore, to provide a visualization of the distribution, Figure 2 depicts the distribution of the logarithm of idiosyncratic volatility (hereinafter LogIV) overlaid with a normal density approximation. Aforementioned results reveal that a lognormal density approximates the distribution of historical monthly idiosyncratic volatility quite well. Idiosyncratic volatility is distributed with right skewness and excess-kurtosis whereas its logarithm is slightly left-skewed and a leptokurtic distribution. Even though it is an attractive property to describe a distribution with only two parameters, however, by implementing Shapiro-Wilk normality test, the hypothesis of a normal distribution of LogIV is rejected. Additionally, low-kurtosis of the distribution suggests the absence of extreme movements in LogIV.

Figure 2: Distribution of Logarithm of Idiosyncratic Volatility



Note: This figure plots the histogram of empirical individual monthly idiosyncratic volatility from FF-3 model. Overlaid on the histogram is the normal density with identical mean and variance to the empirical distribution.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

Table 4: Summary Statistics of Idiosyncratic Volatility and Logarithm of Idiosyncratic Volatility

Variables	Mean	Sd	Skewness	Kurtosis	Max	Min
IV	2.528	1.819	1.935	8.074	18.717	0.013
LogIV	0.707	0.674	-0.259	4.404	2.929	-4.323
N	455946					

Note: This table reports equally-weighted average, standard deviation are other descriptive statistics. IV represents firm-level idiosyncratic volatility and LogIV is the logarithm transformation of IV.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

2.4 Patterns in Average Returns for Idiosyncratic Volatility

Panel A in Table 5 illustrates stock characteristics of volatility quintile portfolios sorted by total volatilities. Portfolios are sorted in an increasing order, thus the fifth portfolio has the highest level of volatility. It shows a clear monotonically increasing pattern of average daily return moving from the lowest total volatility quintile towards the highest quintle. Moreover, the average return in the fifth quintile is more than a double of one in the first quintile. FF-3 alpha is calculated as the constant term from (11) within each quintile. CAPM alpha is also provided according to by only controlling the market excess return. Alpha also tends to increase with the total volatility, this provides a robust evidence by controlling market return, size and value effects. Moreover, the size and market to book ratio of the quintile portfolios also exhibit discernible patterns. The Size column of Panel A shows a negative correlation between total volatility and firm market capitalization, whereas the MV/BV column shows a positive correlation with value factor.

Considerably similar pattern is revealed in Panel B, where the quintile portfolios are sorted by the level of idiosyncratic volatilities instead. The differences of daily return between the portfolio five and one are 0.16% and 0.11% based on equally-weighted averaged return and value-weighted averaged return, respectively. This result diverges from AHXZ (2006) but is consistent with Fu (2009). Subsequently, an economic interpretation would be that investor demands a premium for additional idiosyncratic volatility. Moreover, the similarity between Panel A and B points out strong linkage between total and idiosyncratic volatility. These results pave the way for further analysis and will provide a valuable comparison. Finally, significant FF-3 alpha of “5-1” portfolio suggests possible additional pricing factor caused by idiosyncratic volatility to FF-3 model.

Table 5: Portfolios Sorted by Volatility

Rank	Mean (in %)	Std.Dev.	Size	MV/BV	CAPM Alpha	FF-3 Alpha
			Panel A: Portfolios Sorted by Total Volatility			
			Equally-weighted			
1	0.038	0.612	10879	0.738	0.012**	0.007*
2	0.051	0.979	7659	2.619	0.015**	0.008*
3	0.064	1.212	4678	2.136	0.023**	0.014***
4	0.073	1.489	2408	3.585	0.024**	0.016***
5	0.199	1.885	927	10.025	0.144***	0.136***
5-1	0.162				0.132***	0.129***
			Value-weighted			
1	0.052	0.801	10879	0.738	0.022***	0.019***
2	0.075	1.206	7659	2.619	0.034***	0.030***
3	0.088	1.565	4678	2.136	0.036***	0.034***
4	0.093	2.087	2408	3.585	0.029*	0.029**
5	0.163	2.963	927	10.025	0.084***	0.085***
5-1	0.111				0.062*	0.066*
			Panel B: Portfolios Sorted by Idiosyncratic Volatility			
			Equally-weighted			
1	0.039	0.880	12560	1.082	0.007	0.000
2	0.054	1.110	7453	2.559	0.016*	0.007
3	0.063	1.250	3910	2.197	0.020**	0.011**
4	0.073	1.420	1959	3.704	0.026**	0.019***
5	0.195	1.530	727	9.579	0.149***	0.144***
5-1	0.156				0.143***	0.144***
			Value-weighted			
1	0.058	1.047	12560	1.082	0.021***	0.020***
2	0.075	1.255	7453	2.559	0.031***	0.029***
3	0.087	1.535	3910	2.197	0.037***	0.035***
4	0.090	1.952	1959	3.704	0.032*	0.034**
5	0.163	2.696	727	9.579	0.095***	0.097***
5-1	0.104				0.074**	0.077**

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table reports descriptive statistics by total volatility portfolios and idiosyncratic volatility portfolios. Portfolios are formed monthly by sorting stocks based on total volatility and idiosyncratic volatility. Portfolio 1 has the lowest level of volatilities. Mean and Std.Dev. are equally-weighted or value-weighted monthly average and standard deviation of firm-level daily returns. Size reports average monthly market capitalization and MV/BV reports average monthly market capitalization to book value ratio. The last column refers to the constant term with respect to FF-3 model.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

2.5 Common Pattern in Idiosyncratic Volatility

2.5.1 Cross-Sectional Comparison of Idiosyncratic Volatility

To examine the cross-sectional relationship of idiosyncratic volatility between different characteristic groups, analysis by size, value quintiles and industry classification is provided. This is a methodological replication suggested by Herskovic et al. (2014). Accordingly, stocks have been sorted into five size, value and ten industry portfolios, respectively. Start with the size portfolios, they are determined by the yearly average of firm-level market capitalization. At the June of each year, portfolios are rebalanced. Within each value portfolio *k*, value weighting the monthly idiosyncratic variance from (11) produces the portfolio-level aggregate idiosyncratic variance. Take the square root, that is,

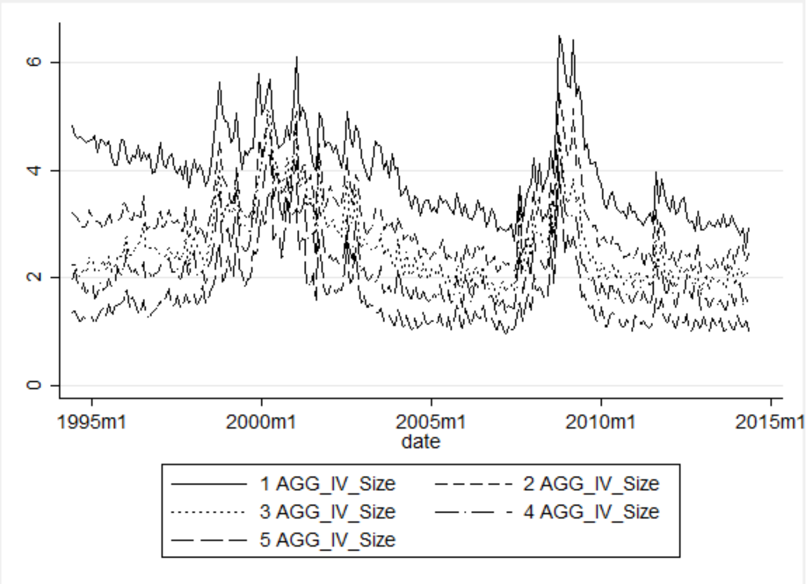
$$\sigma_{k,m} = \sqrt{\sum_{i\in k} w_{i,y} \sum_{t=1}^{T_{i,m}} w_{i,y} \varepsilon_{i,m,t}^{2}} \tag{15}$$

where *m* denotes month and *k* denotes an index for specific portfolio. The weight $w_{i,y}$ is computed using firm *i*'s market capitalization share in period *y*, and *k* is an index of a specific portfolio. Likewise, analogous aggregation technique is applied to value and industry portfolios.

Figure 3 depicts the value-weighted aggregate idiosyncratic volatility over size quintiles. The trajectories reveal highly correlated movement, consequently the average pairwise correlation between these five series duly reaches high value of 0.884. Moreover, stocks with a higher level of idiosyncratic volatility also appear to be associated with smaller capitalization.

Similarly, Figure 4 and Figure 5 plot aggregate idiosyncratic volatility respectively for five value portfolios and ten industry portfolios. Value portfolios are rebalanced yearly by market capitalization to book value ratio and industry portfolios are classified by using separation criteria from Bloomberg database. Analogous to size portfolios, commonalities also exists in value and industry classifications. The analyses report average correlation of 0.905 and 0.791 respectively. Table 6 reports the correlations in more detail. Moreover, there are obvious spikes in trajectories in all three figures around the time of 1997 Asian financial crisis and 2009 global financial crisis.

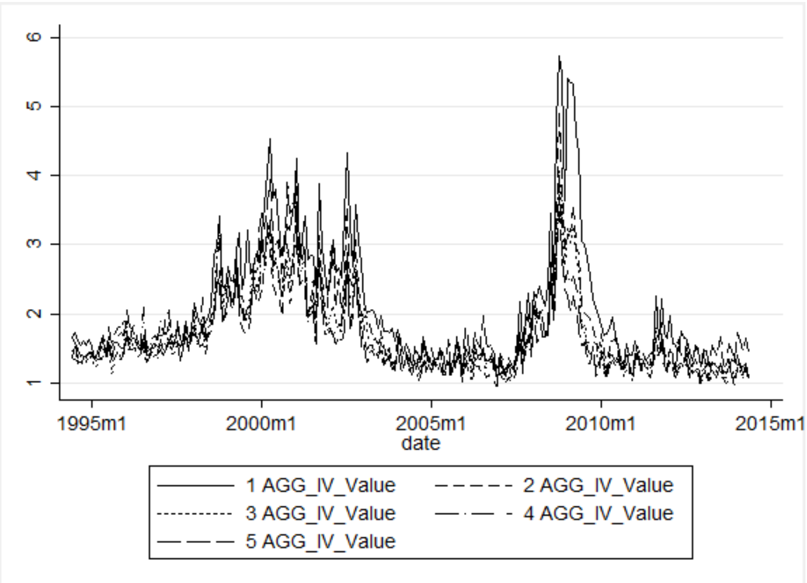
Figure 3: Aggregate Idiosyncratic Volatility by Size Quintile



Note: This figure plots monthly aggregate idiosyncratic volatility within five size groups. Size groups are sorted by yearly average market capitalization. The first portfolio has lowest value of market capitalization.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

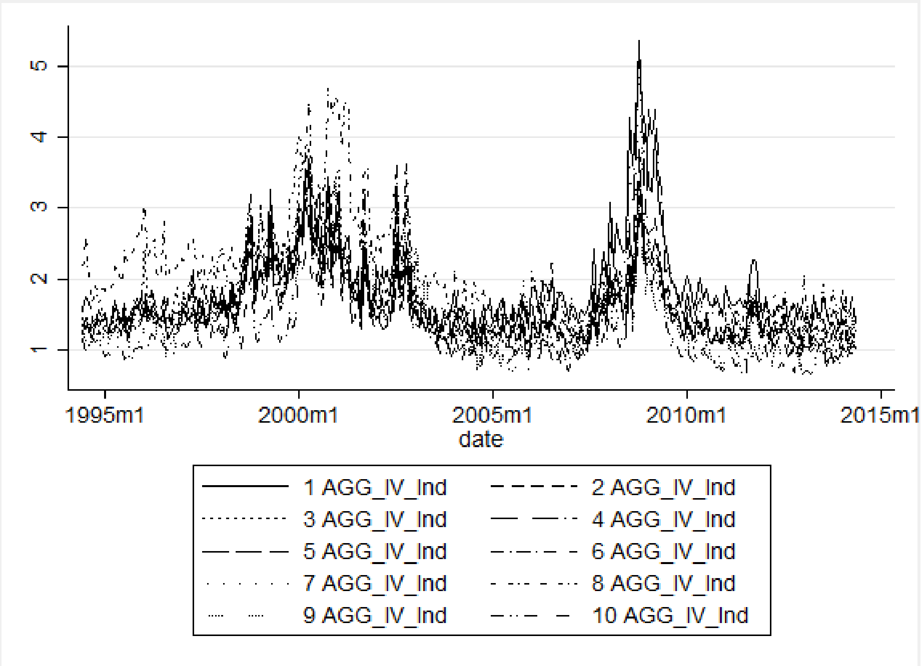
Figure 4: Aggregate Idiosyncratic Volatility by Value Quintile



Note: This figure plots monthly aggregate idiosyncratic volatility within five value groups. Value groups are sorted on yearly average market capitalization to book value ratio. The first portfolio has lowest ratio.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

Figure 5: Aggregate Idiosyncratic Volatility by Industry



Note: This figure plots monthly aggregate idiosyncratic volatility within ten industry groups using the selection criteria on Bloomberg database. The industries are Basic Material, Consumer Goods, Consumer Services, Financials, Health Care, Industrials, Oil & Gas, Technology, Telecommunications and Utilities specifically.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

Arbitrage pricing theory predicts that idiosyncratic risk is purely caused by individual characteristics and can be diversified away. However, these observed commonalities in the cross-sectional aggregate idiosyncratic volatilities suggest otherwise. If idiosyncratic risk shares a potential common trend, then it possibly implies an implicit underlying common factor driving the pattern of idiosyncratic volatility. In addition to the FF-3 factor structure to stock returns, model residual volatilities should inherit supplementary factor model, although commonality in idiosyncratic variance does not directly imply deficiency in FF-3 model. Herskovic et al. (2014) document that common variation of idiosyncratic volatility cannot be explained by potential commonalities within factor model residuals, for example, due to omitted systemic factors. In contrary, Duarte et al. (2014) propose contrasting arguments. Further analysis is needed in order to delve into the cause of commonality in idiosyncratic volatility.

Table 6: Correlation Table of Cross-sectional Aggregate Idiosyncratic Volatility

Panel A: Correlation Matrix by Size Quintile

	Agg_IV_S1	**Agg_IV_S2**	**Agg_IV_S3**	**Agg_IV_S4**	**Agg_IV_S5**
Agg_IV_S1	1				
Agg_IV_S2	0.944	1			
Agg_IV_S3	0.934	0.945	1		
Agg_IV_S4	0.850	0.877	0.953	1	
Agg_IV_S5	0.761	0.780	0.875	0.919	1

Panel B: Correlation Matrix by Value Quintile

	Agg_IV_V1	**Agg_IV_V2**	**Agg_IV_V3**	**Agg_IV_V4**	**Agg_IV_V5**
Agg_IV_V1	1				
Agg_IV_V2	0.939	1.00			
Agg_IV_V3	0.834	0.93	1		
Agg_IV_V4	0.823	0.92	0.9752	1	
Agg_IV_V5	0.804	0.89	0.9571	0.978	1.000

Panel C: Correlation Matrix by Industry

	I1	**I2**	**I3**	**I4**	**I5**	**I6**	**I7**	**I8**	**I9**	**I10**
I1	1.000									
I2	0.775	1.000								
I3	0.688	0.922	1.000							
I4	0.886	0.827	0.762	1.000						
I5	0.682	0.906	0.891	0.741	1.000					
I6	0.803	0.927	0.909	0.855	0.891	1.000				
I7	0.864	0.840	0.776	0.810	0.750	0.840	1.000			
I8	0.497	0.820	0.857	0.581	0.866	0.823	0.639	1.000		
I9	0.586	0.854	0.868	0.652	0.835	0.838	0.678	0.826	1.000	
I10	0.710	0.832	0.796	0.752	0.793	0.856	0.746	0.742	0.816	1.000

Note: This table reports correlation matrix of cross-sectional aggregate idiosyncratic volatility. Panel A shows correlations within size portfolios, Panel B and Panel C reports the same within value and industry portfolios.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

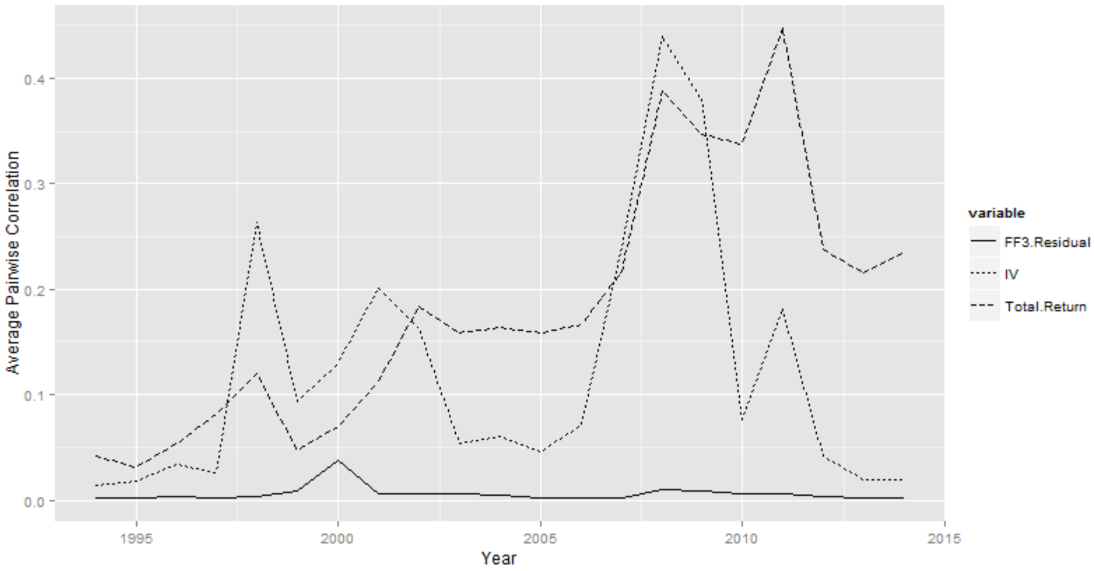
2.5.2 Total Return and Model Residual Comparison

To examine the cause of commonality in cross-sectional idiosyncratic volatility, firstly one needs to know the level of correlation among FF-3 factor model residuals. Analogous to Herskovic et al. (2014), annual average pairwise correlations of stock returns and FF-3 residuals are calculated. Correspondingly average pairwise correlation is defined as the weighted average of the lower triangular elements from a full correlation matrix. Construct $\rho_{i,j}$ as the correlation between stock i and j, w_i as the weight of stock i. As a result, average pairwise correlation is (Tierens & Anadu, 2004):

$$\rho_{av} = \frac{2 \sum_{i=1}^{N} \sum_{j>i}^{N} w_i w_j \rho_{i,j}}{1 - \sum_{i=1}^{N} w_i^2} \tag{16}$$

In order to provide a direct comparison, average pairwise correlation of firm-specific idiosyncratic volatilities is also computed in addition to total returns and FF-3 residuals (Herskovic, Kelly, Lustig, & Nieuwerburgh, 2014). For simplified calculation, only equal weights are used.

Figure 6: Average Pairwise Correlation



Note: This figure plots the annual average pairwise correlation for total returns, idiosyncratic residuals and idiosyncratic volatilities. Idiosyncratic volatility is the standard deviation of FF-3 model residuals. The mean level of average pairwise correlation are 18.15%, 12.24% and 0.60% for total return, idiosyncratic volatilities and idiosyncratic returns respectively over the 1994-2014 sample.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

Figure 6 depicts the trajectories of average pairwise correlation for total returns, idiosyncratic residuals from FF-3 estimation and idiosyncratic volatilities which are calculated as the monthly standard deviation of FF-3 idiosyncratic residuals. Accordingly, total returns share substantially higher correlation. Especially at crisis time, it reaches maximum of nearly 50%. On the other hand, average idiosyncratic residual correlations remains at a steady low level around 0.6%. This result resembles one concluded from Herskovic et al. (2014). Moreover, the average correlation for idiosyncratic volatilities remains at a relatively high level, however this pattern is not consistent with time, during the time around 1995, 2005 and after 2012, the average correlations remains at a low level. Interestingly, it has a trajectory revealing a unique pattern differs from the other two.

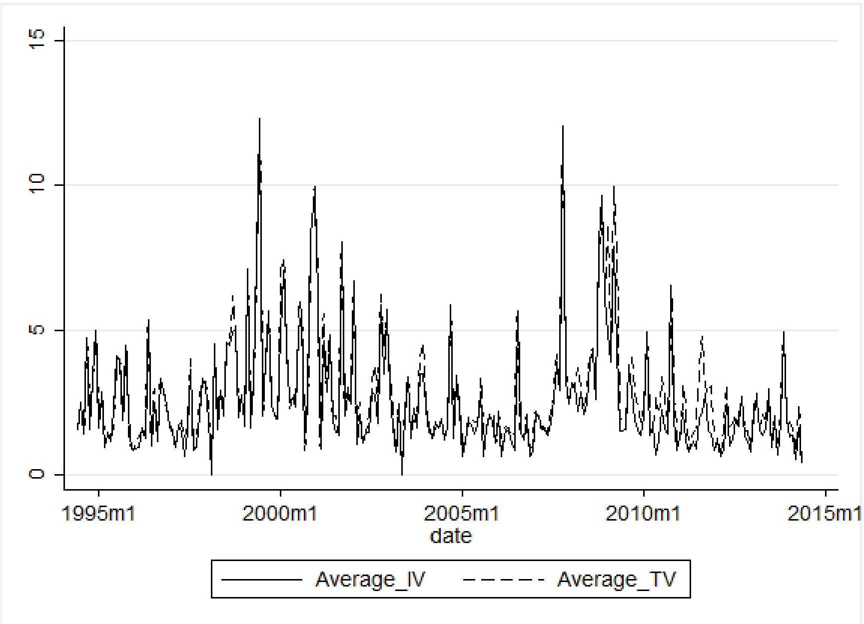
Therefore, the evidence of co-movement in idiosyncratic volatilities is not as strong as previously suggested by cross-sectional comparison.

As a result, Figure 6 derives two implications. First, FF-3 model appears to absorb the majority of systemic determinant of stock price, in other words, most of the commonalities in stock returns are absorbed by proposed factors. Secondly, neither stock return correlation nor idiosyncratic residual correlation reveals the cause of idiosyncratic volatility co-movement. As an implication, a factor structure for stock returns does not capture the factor structure of idiosyncratic volatility.

2.5.3 Total Volatility and Idiosyncratic Volatility Comparison

Notwithstanding FF-3 factors absorb majority of stock return correlations, the factor model fails to explain total return volatility. Figure 7 provides a straightforward comparison between average total return volatility and average idiosyncratic volatility. Apparently two trajectories share nearly identical variation. Pairwise correlation between the two is reported as 0.966.

Figure 7: Average Volatility



Note: This figure depicts cross-sectional average monthly individual volatility for total and idiosyncratic returns. Average_IV denotes monthly average of idiosyncratic volatility, Average_TV denotes the one of total volatility.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

Once again, it is evident that market portfolio factor, size factor and value factor can barely capture the dynamics of return volatilities. It is still up to question that whether the commonality in idiosyncratic volatility can serve as a missing pricing factor. However, one can find a noticeable difference between the commonality in returns and the commonality in volatilities. This suggests there might be a divergent factor pattern inherited in firm-level volatilities.

3 COMMON COMPONENT OF IDIOSYNCRATIC VOLATILITY

3.1 Extracting Common Component from Individual Idiosyncratic Volatility

3.1.1 Asymptotic Principal Component Analysis

Principal Component Analysis (hereinafter: PCA) is a statistical procedure decompose the variance structure of a vector time series into a set of orthogonal variables. The methodology is designed so that the first component will explain the largest portion of the variance, and each successive component has the greatest subsequent variance under the restriction that retrieved principal components are uncorrelated. Given an $T \times I$ dimensional matrix $\boldsymbol{IV} = (IV_1, \dots, IV_I)'$ from (12) with covariance matrix $\sum_{IV}$ for I stocks, where IV_i denotes the time-series vector of stock i. Then a PCA is intended to use few variables to replicate the dynamics of $\sum_{IV}$ (Tsay, 2010). Yet a major limitation with PCA that it assumes the number of variables is smaller than the number of observations. To cope with the situation encountered in this thesis, where the number of stocks greater than the number of monthly observations, as suggested by Duarte et al. (2014), one can use the asymptotic principal component analysis (hereinafter: APCA) method introduced by Connor and Korajczyk (1988).

APCA resembles traditional PCA besides that it relies on asymptotic result as the number of cross-section N (stocks) grows large. According the eigenvector analysis of a $T \times T$ matrix $\widehat{\Omega}_T$ forms the basis of APCA (Tsay, 2010):

$$\widehat{\boldsymbol{\Omega}}_T = \frac{1}{I}(\boldsymbol{IV} - \boldsymbol{1}_T\overline{\boldsymbol{IV}}')(\boldsymbol{IV} - \boldsymbol{1}_T\overline{\boldsymbol{IV}}')' \qquad (17)$$

Where $\overline{\boldsymbol{IV}}' = (\overline{IV}_{\boldsymbol{1}}, \dots, \overline{IV}_{\boldsymbol{I}})'$ with $\overline{IV}_i = \left(\boldsymbol{1}_{\boldsymbol{T}}' \boldsymbol{IV}_i\right)/T$ as the sample mean of ith stock, and $\boldsymbol{1}_T$ is a T-dimensional vector of ones. Principal components attained as eigenvectors from $\widehat{\boldsymbol{\Omega}}_T$. Assume first k eigenvectors of $\widehat{\boldsymbol{\Omega}}_T$ consists a $k \times T$ matrix $\widehat{\boldsymbol{F}}_T$. Further, the tth column of $\widehat{\boldsymbol{F}}_t$ denotes as $\widehat{\boldsymbol{f}}_t$, consequently refined estimation $\boldsymbol{f}_t$ identify k principal components. Connor and Korajczyk describe the procedure of estimation as follows (Tsay, 2010):

a. Calculate initial estimate of $\hat{f}_t$ using sample covariance matrix $\widehat{\boldsymbol{\Omega}}_T$ for $t = 1, \ldots, T$.

b. Use ordinary least squares estimation on (18), retrieve $\boldsymbol{\beta}_i = (\beta_{i1}, \ldots, \beta_{ik})$ and residual variance $\hat{\sigma}_i^2$

$$IV_{it} = \alpha_i + \boldsymbol{\beta}_i \hat{\boldsymbol{f}}_t + \epsilon_{it},\ t = 1, \ldots, T \tag{18}$$

c. Build diagonal matrix $\widehat{\mathbf{D}} = diag\{\hat{\sigma}_1^2, \ldots, \hat{\sigma}_I^2\}$ and rescale idiosyncratic volatilities as $\boldsymbol{IV}_* = \boldsymbol{IV}\widehat{\mathbf{D}}^{-\frac{1}{2}}$.

d. Calculate the adjusted $T \times T$ covariance matrix using $\boldsymbol{IV}_*$ as

$$\widehat{\boldsymbol{\Omega}}_* = \frac{1}{I}(\boldsymbol{IV}_* - \boldsymbol{1}_T \overline{\boldsymbol{IV}}_*{}')(\boldsymbol{IV}_* - \boldsymbol{1}_T \overline{\boldsymbol{IV}}_*{}')' \tag{19}$$

In the end, refined estimate of $\boldsymbol{f}_t$ can be obtained with eigenvector analysis of $\widehat{\boldsymbol{\Omega}}_*$.

3.1.2 Idiosyncratic Volatility Decomposition

In this section, three approaches are used to extract common pattern within firm-level idiosyncratic volatilities. Duarte et al. (2014) use APCA method to obtain five volatilities factors whereas Herskovic et al. (2014) use equally-weighted average of cross-sectional volatilities. Table 7 reports factor model estimations for monthly firm-level idiosyncratic volatilities in order to determine the amount of total, cross-sectional and time-series variation in individual idiosyncratic volatility that is explained by the common idiosyncratic volatility factors. The second column uses equally-weighted average of individual idiosyncratic volatilities as a proxy for common component in idiosyncratic volatility. While the third and fourth column reports the results based on value-weighted factor and APCA factors.

The equally-weighted average returns adjusted R-squared of 0.137, which is the highest among three estimation methods. Estimation with equally-weighted average also reports the only insignificant t-statistics of the constant term. Surprisingly, by including more factors, APCA method doesn’t improve goodness of fit. One can surmise it is due to the methodology constraint of APCA method. Though APCA manages to solve low observation limitation incurred by PCA method, APCA is still limited to another constraint, which enforce matrix $\boldsymbol{IV}$ to have full observation.

Table 7: Common Factor Estimation

	(Equally-weighted) IV	(Value-weighted) IV	(APCA) IV
CIV	1.000***	1.159***	
	(268.67)	(255.85)	
APCA1			10.01***
			(262.92)
APCA2			-0.408***
			(-10.41)
APCA3			-0.889***
			(-20.12)
APCA4			-0.568***
			(-13.70)
APCA5			-0.526***
			(-14.19)
Constant	2.31e-09	0.766***	2.580***
	(0.00)	(104.52)	(1004.23)
N	455946	455946	455946
adj. R^2	0.137	0.126	0.135

t statistics in parentheses

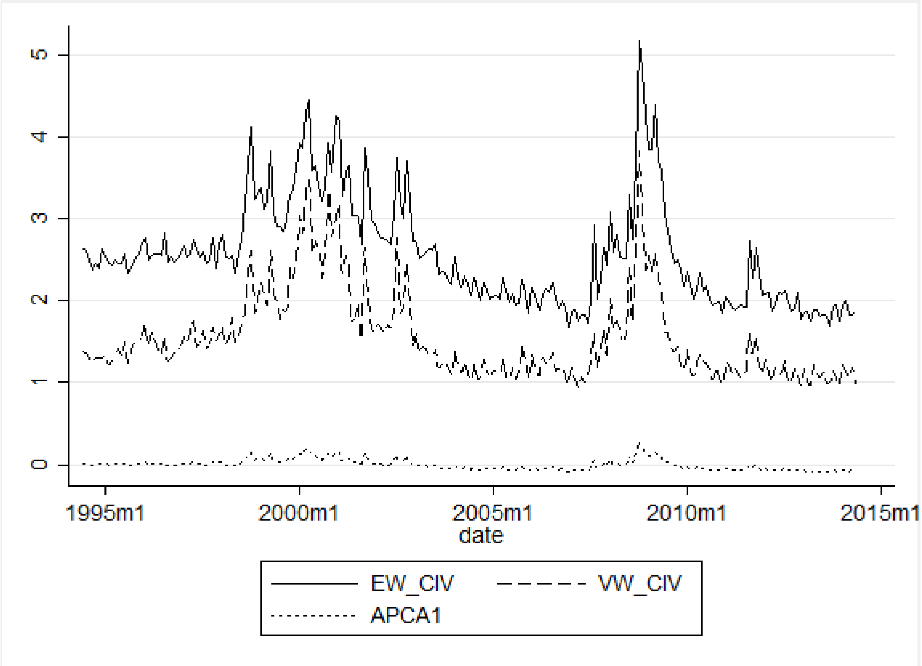
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table reports monthly volatility regression using equally-weighted CIV, value-weighted CIV and APCA 5 factors respectively. Equally-weighted CIV is defined as equally-weighted cross-sectional average of firm-level idiosyncratic volatilities within each month, Value-weighted CIV is the corresponding term weighted using market capitalization instead. APCA produces five common components of idiosyncratic volatility. The regressions has a general form of $IV_{i,m} = intercept + \sum_{k=1}^{K} loading_k factor_{k,m} + \varepsilon_{i,m}$. Adjusted R-squared, factor loadings and corresponding t-statistics are reported.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

In order to cope with this limitation, one needs to remove columns contains any empty value in a matrix. However by doing so one can lose valuable data of the market. As a result, only 1074 out of 2719 stocks can be used for APCA computation. In contrast, APCA reports adjusted R-squared of 0.184 from the regression on 1074 stocks. Figure 8 plots the time series of equally-weighted common idiosyncratic volatility (hereinafter CIV), value-weighted CIV and the first common component of idiosyncratic return volatility from APCA. Despite the visual misconception, the first common component from APCA still shares a correlation of 98.54% with equally-weighted CIV.

Figure 8: Time Series of Common Component



Note: This figure plots the time series of equally-weighted CIV, value-weighted CIV and the first component of idiosyncratic volatility from APCA for the whole sample from June 1994 to June 2014.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

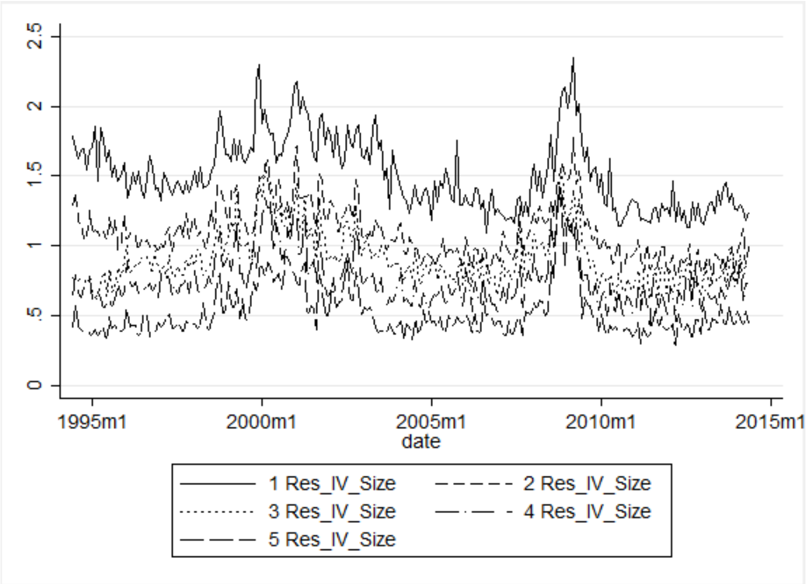
Lastly, equally-weighted CIV is chosen as a proxy for commonality in monthly firm-level idiosyncratic volatilities, for two reasons. Firstly, estimation on equally-weighted CIV results in the highest level of fit. Furthermore, value weighting scheme can conceal the effect on idiosyncratic volatility from small firms (Plyakha, Uppal, & Vilkov, 2014).

3.2 Characteristics of the CIV

3.2.1 CIV Removal

In order to investigate whether CIV effectively captures the commonalities in monthly individual idiosyncratic volatilities, the behavior of residuals, from regressing individual idiosyncratic volatilities on CIV is examined in detail. By implementing the regression $IV_{i,m} = \alpha_i + b_i CIV_m + e_{i,m}$, one can study the idiosyncratic behavior of stock return volatilities after removing the systematic factor. If CIV can explain the systemic variation of firm-level idiosyncratic volatilities, thereafter the disturbance $e_{i,m}$ should not reveal high degree of commonality. Figure 9 depicts the cross-sectional aggregate of individual disturbance $e_{i,m}$ by size quintiles. Comparing to Figure 3 from the previous section, trajectories in Figure 9 shows slightly less clustered pattern. The series by size quintiles have the average correlation of 0.776.

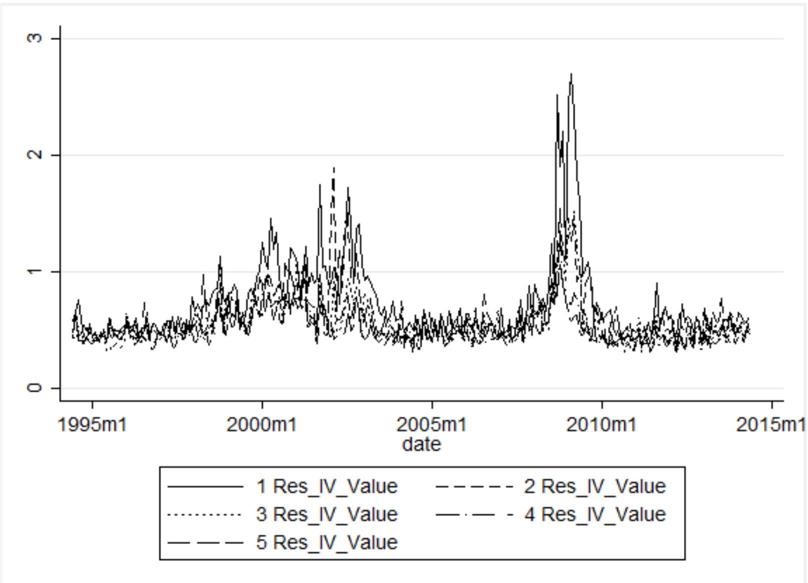
Figure 9: CIV Residuals by Size Quintile



Note: This figure plots residuals from regressing individual volatilities on CIV averaged within five size portfolios. The regression has the form of $IV_{i,m} = \alpha_i + b_i CIV_m + e_{i,m}$. Size portfolios are sorted on yearly average market capitalization. The first portfolio has lowest value of market capitalization.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

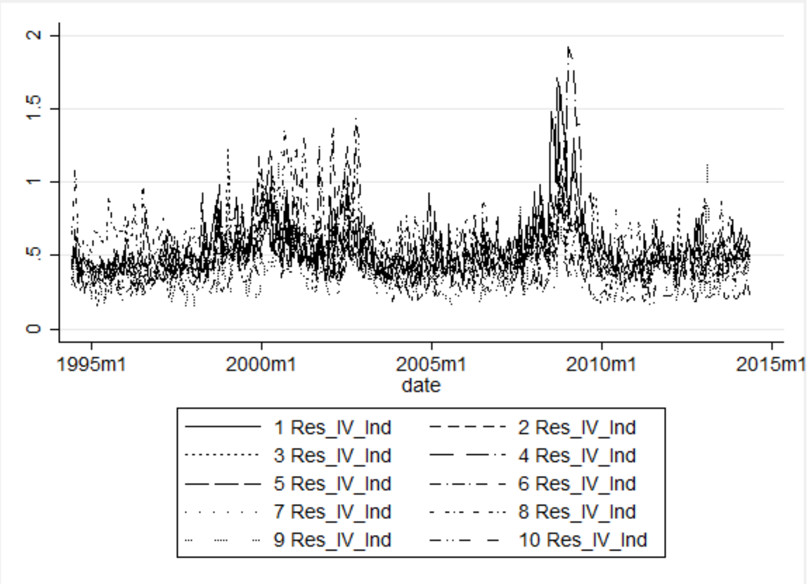
Figure 10: CIV Residuals by Value Quintile



Note: This figure plots residuals from regressing individual volatilities on CIV averaged within five value portfolios. Value portfolios are sorted on yearly average market capitalization to book value ratio. The first portfolio has lowest ratio.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

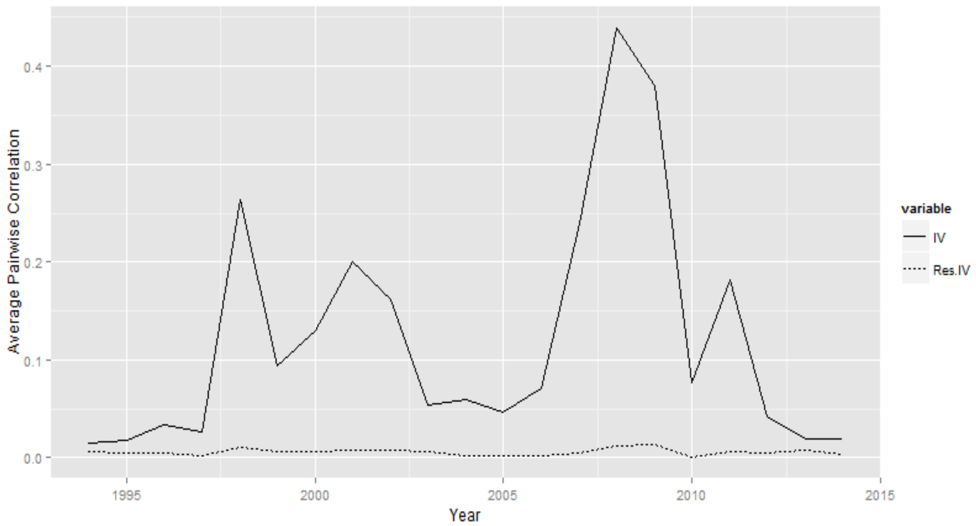
Figure 11: CIV Residuals by Industry



Note: This figure plots residuals from regressing individual volatilities on CIV averaged within ten industry portfolios using the selection criteria on Bloomberg database. The industries are Basic Material, Consumer Goods, Consumer Services, Financials, Health Care, Industrials, Oil&Gas, Technology, Telecommunications and Utilities specifically.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

Figure 12: Average Pairwise Correlation



Note: This figure plots the annual average pairwise correlation for idiosyncratic volatilities and residuals from regression of monthly firm-level idiosyncratic volatility on CIV. The mean level of average pairwise correlation are 12.23% and 0.57% respectively.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

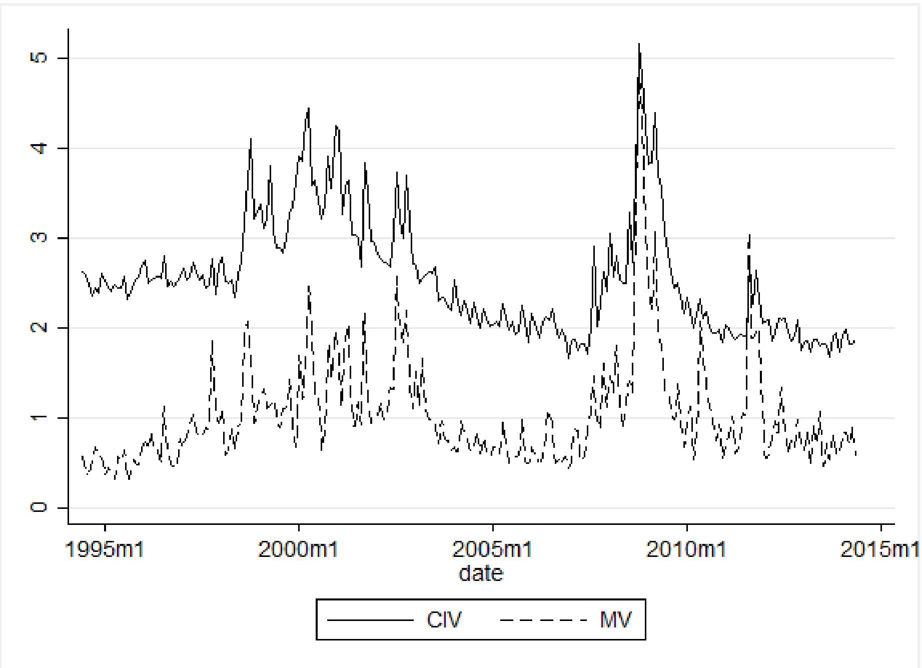
Figure 10 and Figure 11 show analogous analysis regarding value quintiles and industry classifications. The average correlations are respectively 0.655 and 0.414. The trajectories show more disordered pattern than the original figures. Cross-sectional comparisons does not provide convincing evidence that CIV eliminates all the commonalities in firm-level idiosyncratic volatilities.

On the other hand, Figure 12 provides a more direct comparison. The residual term lies well below the trajectory of idiosyncratic volatility average pairwise correlations. Apparently CIV captures nearly all of the common variation of monthly idiosyncratic volatilities. Therefore, CIV validates as a proxy capturing commonality of monthly idiosyncratic volatility.

3.2.2 CIV and Market Variance

Figure 13 and Figure 14 replicate the finding regarding CIV and market variance by Herskovic, Kelly, Lustig and Nieuwerburgh (2014). The sum of MrkRF and RF from Kenneth French's data library is used to stand for value-weighted market return.

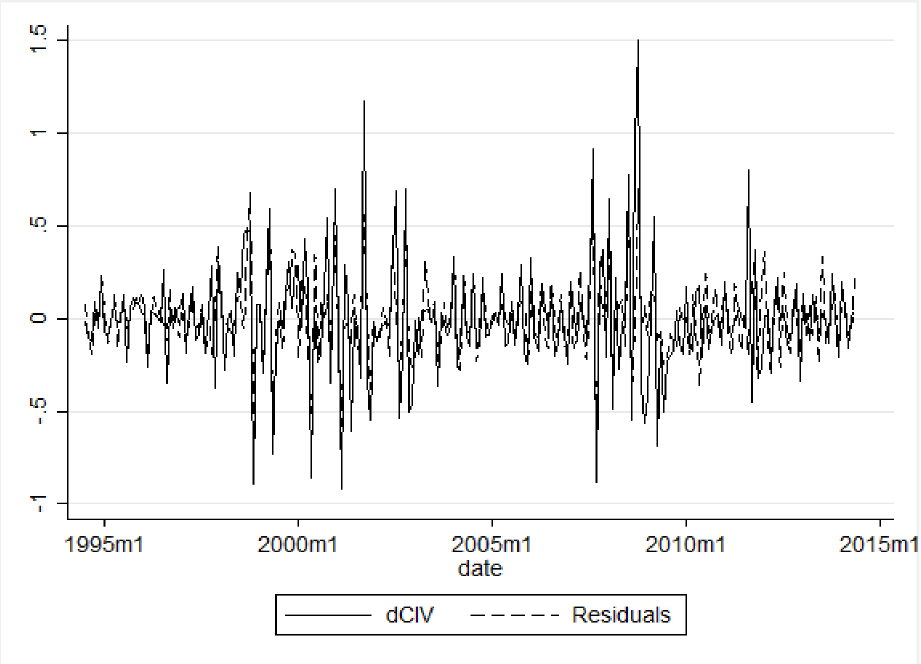
Figure 13: Time Series of Volatility Levels



Note: This figure plots the monthly equally-weighted average firm-level idiosyncratic volatility (CIV) and monthly value-weighted average volatility of market return (MV).

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

Figure 14: Time Series of Volatility Changes



Notes: This figure plots the changes in monthly equally-weighted average firm-level idiosyncratic volatility (dCIV) and residuals from regression of dCIV on changes in monthly value-weighted average market volatility.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

Figure 13 plots time series of CIV and volatility of the market return. Naturally the plot shows substantial similarity between two series. Correlation between the two is 0.722. Analogously, changes in CIV has a correlation of 0.711 with changes in market volatility. More intriguingly, after removing market volatility from CIV, the residual still have a high level of correlation with CIV. Figure 14 depicts CIV innovation (proxied by ΔCIV), as well as the residuals from regressing ΔCIV on market volatility innovation (proxied by ΔMV). Surprisingly, these two series shares correlation of 0.704. The corresponding correlation between CIV and its residual orthogonal to market volatility is 0.692. This implies CIV and market variance are, although comparable, however still in a large difference from each other.

3.2.3 Unit Root Test

Many financial time series are known for being persistent over time. In other words, many time series exhibit non-stationarity or trending pattern. Therefore, an essential econometric task is to explore the trend and take transformation to de-trend if necessary. In order to discover the autocorrelation structure of these volatility series, one needs to perform unit root test to help determine an appropriate method for trend removal. Several tests have been developed to investigate the stationarity of a time series. One of the most representative tests is Augmented Dickey-Fuller test.

Starting with Dickey-Fuller (hereinafter DF) test, first consider a first-order autoregressive process: (Greene, 2003)

$$y_t = \mu + \rho y_{t-1} + \varepsilon_t;\ \ \varepsilon_t \sim N(0, \sigma_\varepsilon^2) \tag{20}$$

Subsequently, DF tests the null hypothesis $H_0: \rho = 1$, against the alternative hypothesis $H_a: \rho < 1$. After subtracting both sides from (20) yields

$$\Delta y_t = \mu + (\rho - 1) y_{t-1} + \varepsilon_t = \mu + \theta y_{t-1} + \varepsilon_t \tag{21}$$

Therefore, the null hypothesis now turns into $H_0: \theta = 0$, against alternative $H_a: \theta < 0$. Alternative hypothesis indicates the absence of unit root in tested series. Dickey and Fuller gives a set of asymptotic critical values for the related t-test or F-test (Wang, 2008).

However DF test relies on assumption that the error term is independent and identically distributed (hereinafter i.i.d), in case disturbance is not a white noise process, augmented Dickey-Fuller (ADF) test can be applied to accommodates serial correlation in residuals. Extending the model from (20), one has

$$y_t = \mu + \rho y_{t-1} + \rho_1 y_{t-2} + \ldots + \rho_p y_{t-p} + \varepsilon_t;\ \varepsilon_t \sim N(0, \sigma_\varepsilon^2) \tag{22}$$

Analogous to before, subtracting both sides from (22) gives

$$\Delta y_t = \mu + \rho^* y_{t-1} + \sum_{j=1}^{p} \phi_j \Delta y_{t-j} + \varepsilon_t \tag{23}$$

Where $\phi_j = -(\rho_{j+1} + \cdots + \rho_p)$ and $\rho^* = (\rho_1 + \cdots + \rho_p) - 1$. The estimators are obtained by performing OLS estimation on (23). Hence ADF tests H_0: $\rho^* = 0$ against H_a: $\rho^* < 0$ using t-statistics of the coefficient ρ^* from OLS (Lütkepohl & Krätzig, 2004).

Additionally, the lag length p needs to be determined in order to use ADF test. On one hand, too few lags can leave the remaining error autocorrelation bias the test. On the other hand, too many lags can weaken the power of the test. Therefore, to determine the optimal number of p, one can conduct a recursive test starting from some higher-order (Lütkepohl & Krätzig, 2004). Alternatively, one can implement Akaike or Schwarz information criteria to determine the number of lags (Greene, 2003).

Accordingly, by implementing ADF test for CIV with monthly frequency, the null hypothesis of a unit root of is rejected. Thus, monthly CIV is a stationary process and shows mean-reverting property.

3.3 Patterns in Average Returns for CIV

To investigate the asset pricing implication of CIV, one can analyze whether stocks with different sensitivities to CIV lead to different levels of average returns. Since CIV is estimated at monthly frequency, thus monthly return is used for the asset pricing analysis. In order to estimate the sensitivity of stock return to CIV, individual excess returns are regressed on market excess returns and CIVs. The estimation follows the empirical regression

$$R_{it}\text{-}Rf_t = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{CIV} CIV_t + \varepsilon_{it} \tag{24}$$

Minimal factors in the model are used in order to reduce the noise incurred by controlling other effects, such as size or value effect. However, these two FF-3 factors and other potential effects will be examined to test the robustness of the return CIV relationship. To begin with, only constant loadings are measured by using ordinary least square regression on (24), thereafter a set of quintile portfolios is constructed by sorting loadings on CIV increasingly. In order to have sufficient observation for individual regression, only stocks with at least one full yearly observations is included.

Table 8 reports several descriptive statistics for quintile portfolios sorted by CIV loadings. Portfolios in Panel A are constructed with equal weights, while being constructed by using market capitalization as value weights in Panel B. The first two columns document mean and standard deviation of the monthly firm-level return. Following two columns report average market capitalization and average market value to book value ratio. The average level of loadings on CIV increase monotonically from -2.489 to 3.870 for portfolio one to five. Although the firm-level loading estimations are constant over time, portfolios are still updated monthly to cope with increasing number of firms which are included through time. Last but not least, the last two columns report the constant term of the regression formed on single-factor CAPM and FF-3 model respectively.

Accordingly, both equally-weighted and value-weighted average returns increase with CIV loadings. Although equally-weighted returns demonstrate monotonically stronger pattern, whereas in Panel B, average returns first decrease as moving from portfolio 1 to 3. This implies that investors require that stocks with higher sensitivity to common idiosyncratic volatility be compensated with a higher premium. Similarly, by eliminating market return, size and value effects, as shown in the columns of CAPM alpha and FF3 alpha, average returns still hold similar pattern by CIV loading portfolios. In particular, the rows of 5-1 illustrate trading strategy of combining longing portfolio 5 and shorting portfolio 1 as a zero-investment portfolio.

Table 8: Portfolios Sorted by CIV Loadings

Portfolio	Mean	Std.dev.	Size	MV/BV	CIV Loading	CAPM Alpha	FF3 Alpha
				Panel A: Equally-weighted			
1	1.174	5.531	1310	-0.711	-2.849	0.327	0.117
2	1.330	4.256	7174	7.512	-0.438	0.583***	0.369***
3	1.419	4.417	7254	2.611	0.260	0.628***	0.430***
4	1.536	5.233	6735	2.415	1.079	0.628***	0.463***
5	2.146	8.312	3990	5.388	3.870	0.896**	0.932***
5-1	0.972					0.569	0.814**
				Panel B: Value-weighted			
1	1.367	5.057	1310	-0.711	-2.849	0.571**	0.366*
2	1.212	3.746	7174	7.512	-0.438	0.566***	0.476***
3	1.256	4.341	7254	2.611	0.260	0.448***	0.402***
4	1.352	4.781	6735	2.415	1.079	0.482***	0.493***
5	1.848	7.692	3990	5.388	3.870	0.639**	0.797***
5-1	0.481					0.068	0.431

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table reports descriptive statistics of quintile portfolios formed by sorting loadings on equally-weighted common idiosyncratic volatility. CIV loadings are estimated by regressing excess monthly firm-level returns on CIV, controlling for the market excess return factor as in (24). Portfolios are sorted on β_i^{CIV} from the lowest (portfolio 1) to the highest (portfolio 5). The columns Mean and Std.Dev. report average and standard deviation of monthly return within each quintile. In Panel A, equally-weighted scheme is used, whereas in Panel B, value weights are implemented. Size reports average market capitalization, MV/BV reports average market capitalization to book value ratio. The row “5-1” relates to the spread between portfolio 5 and 1. The CIV Loadings column reports the average β_i^{CIV} within each quintile. The Alpha columns refer to the constant term with respect to the CAPM one-factor and Fama-French three-factor model. The asterisks denote the significance level. The sample spans time period from June 1994 to June 2014.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

Correspondingly the 5-1 spread in average return between the highest CIV loading and the lowest CIV loading are 0.972 and 0.481 for equally-weighted and value-weighted return. Likewise, CAPM and FF-3 alphas are also documented to be positive. However, only the alpha from FF3 model using value-weighted scheme reports positive spread significant at 1% level. The standard deviation, first decreases from moving quintile 1 to 2 and then increases. Moreover, the average market capitalization first rises then drops whereas the average market to book value ratio does not reveal discernible pattern.

3.3.1 Robustness to Estimation Frequency

In this subsection, the robustness of previous results to estimation method is investigated. In the previous subsection, only constant loadings are estimated through time. However, coefficients may potentially vary over time. In order to take time-varying coefficients into account as well to ensure sufficient observations for each regression, a five-year estimation window is implemented. Thereafter factor loadings will be estimated conditional to specific estimation window. Accordingly the sample period is separated into four subsamples with equal length.

Table 9: Portfolios Sorted by CIV Loadings using Time-Varying Coefficients

Portfolio	Mean	Std.dev.	Size	MV/BV	CIV Loading	CAPM Alpha	FF3 Alpha
				Panel A: Equally-weighted			
1	1.330	6.087	2213	4.842	-6.447	0.446	0.255
2	1.402	4.428	5793	2.642	-1.793	0.634***	0.442***
3	1.395	4.290	7829	3.368	-0.144	0.625***	0.438***
4	1.510	4.982	7103	2.339	1.530	0.647***	0.473***
5	1.967	8.678	3619	4.226	6.466	0.710*	0.702**
5-1	0.637					0.264	0.447
				Panel B: Value-weighted			
1	1.314	5.801	2213	4.842	-6.447	0.413	0.326
2	1.257	4.089	5793	2.642	-1.793	0.555***	0.455***
3	1.315	4.193	7829	3.368	-0.144	0.545***	0.507***
4	1.365	4.644	7103	2.339	1.530	0.523***	0.493***
5	1.688	8.151	3619	4.226	6.466	0.455	0.474
5-1	0.374					0.041	0.147

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table documents analogous report to Table 8. The analysis only differs by implementing time-dependent regression. The sample is split into four subsamples with equal length. Each subsample spans five years. Within each subsample, CIV loadings are estimated by regressing excess monthly firm-level returns on CIV, controlling for the market excess return factor as in (24). In Panel A, equally-weighted scheme is used, whereas in Panel B, value weights are implemented. Portfolios are sorted on β_i^{CIV} from the lowest (portfolio 1) to the highest (portfolio 5) each month.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

Loadings on CIV are estimated by using (24) within each subsample. Finally, stocks are sorted into quintile portfolios by CIV loadings each month. Table 9 reports the results by implementing time-varying estimation method. Similar to Table 8, Panel A uses equally-weighted average returns and Panel B uses value-weighted average returns. The pattern of average returns in Table 8 remains, however the difference between portfolio 5 and 1 decreases in magnitude to 0.637 in Panel A and 0.374 in Panel B. The spread of CAPM and FF-3 alphas also decreased for portfolio 5 and 1. Moreover, standard deviation shows the same pattern as the average return. Thus, by using a more frequent estimation of factor loadings, the effect of sensitivity of CIV to stock returns weakens.

While the pattern of 5-1 spread sorted on CIV betas is very consistent, one cannot claim the difference is due to systemic risk. Therefore, the pattern of CIV loadings and average returns will be investigated controlling for other potential pricing effects.

3.3.2 Robustness to Size and Value Effects

Commonly speaking, small company stocks tend to vary differently than the big ones. A usual perception argues that the small companies bear relatively higher risk and the risk should come at a price. Therefore, stocks with lower capitalization is associated with higher average level of return. Analogously, value stocks accompanied with low price-to-book ratio tend to have higher future growth potential. Empirically, small and value stocks outperform big and growth stocks. These anomalies are the foundation of FF-3 factor model (Fama & French, 1993). Is it possible that the effect of CIV exposure to average returns is partially caused by size and value effects?

Table 10: Portfolio sorted by CIV loadings and Size Quintiles

	Size Quintiles						
	1	**2**	**3**	**4**	**5**	**5-1**	**t(5-1)**
1	0.763	1.482	1.574	1.372	1.392	0.629	1.247
2	1.235	1.468	1.294	1.484	1.293	0.058	0.140
3	1.204	1.668	1.493	1.442	1.320	0.116	0.252
4	1.317	1.562	1.783	1.561	1.386	0.070	0.130
5	1.334	2.248	2.500	2.422	2.098	0.764	1.014
5-1	0.570	0.766	0.926	1.049	0.706		
t(5-1)	0.910	1.113	1.325	1.558	1.077		

Note: This table reports equally-weighted average returns sorted on CIV loadings and size quintiles. The columns correspond to the CIV loadings dimension. CIV loadings are estimated as constants throughout whole sample period. Market capitalization is used as proxy for size characteristics. CIV portfolios are rebalanced monthly whereas size portfolios are rebalanced annually. 5-1 reports the spread between portfolio 5 and 1, t(5-1) reports corresponding t-statistics. The sample spans time period from June 1994 to June 2014.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

Table 10 reports equally-weighted average returns of CIV portfolios controlling for size effects. CIV portfolios are formed as mentioned previously, first CIV loadings are estimated by implementing regression on (24), then stocks are sorted into 5 quintile portfolios by their loadings. Portfolios are rebalanced at the end of each month. Size portfolios are sorted by the yearly average of firm-level market capitalization from the lowest (portfolio 1) to the highest (portfolio 5). Accordingly, stocks with high exposure to CIV continues to yield higher returns. The differences of the average return between the fifth CIV portfolio and the first CIV portfolio range from 0.57 to 1.04 controlling for size effects. However, the spreads are not all significant for all the size quintiles. Reversely, controlling for CIV effects, there is no evidence that small firms outperform large firms. Yet this is consistent with diminishing size effect since 90's as documented in recent literatures.

Likewise, Table 11 controls for the value effects. Value portfolios are sorted by the yearly average of firm-level market capitalization to book value ratio. By controlling value effects, the differences of CIV portfolios 5 to 1 remain positive, however, weaken in magnitude. The CIV loadings spreads range from 0.27 to 1.11. Interestingly, this is consistent with documented evidence that value stocks outperformed growth stocks from the 90's.

Table 11: Portfolio sorted by CIV loadings and Value Quintiles

	Value Quintiles						
	1	**2**	**3**	**4**	**5**	**5-1**	**t(5-1)**
1	0.451	0.845	1.406	1.515	2.172	1.720	2.795
2	0.852	1.147	1.406	1.549	1.883	1.032	2.263
3	0.663	1.169	1.487	1.716	2.239	1.577	3.239
4	1.011	1.156	1.394	1.646	2.391	1.381	2.430
5	0.993	1.339	1.678	2.317	3.286	2.293	2.779
5-1	0.541	0.494	0.272	0.802	1.114		
t(5-1)	0.808	0.787	0.436	1.189	1.425		

Note: This table reports equally-weighted average returns sorted on CIV loadings and value quintiles. The columns correspond to the CIV loadings dimension. CIV loadings are estimated as constants throughout whole sample period. Market capitalization to book value ratio is used as proxy for size characteristics. CIV portfolios are rebalanced monthly whereas value portfolios are rebalanced annually. 5-1 reports the spread between portfolio 5 and 1, t(5-1) reports corresponding t-statistics. The sample spans time period from June 1994 to June 2014.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

Furthermore, CIV loadings are estimated by also controlling size and value effect based on (24).

$$R_{it}\text{-}Rf_t = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \beta_i^{CIV} CIV_t + \varepsilon_{it} \qquad (25)$$

Table 12 reports the results by implementing (25), the result is comparable with only controlling for market excess return. The spread of mean return decreases from 0.93 to 0.85 from Table 8, whereas the spread of FF-3 alpha decreases from 0.75 to 0.63. Therefore, the association of high CIV loading and high return is not mainly driven by size or value effects.

Table 12: Portfolios Sorted by CIV Loadings Controlling for Size and Value Effect

Portfolio	Mean	Std.Dev.	CIV Loading	CAPM Alpha	FF3 Alpha
1	1.203	5.698	-2.435	0.341	0.170
2	1.378	4.438	-0.255	0.591***	0.409***
3	1.448	4.442	0.393	0.655***	0.468***
4	1.566	5.074	1.105	0.677***	0.506***
5	2.056	7.833	3.035	0.842***	0.806***
5-1	0.854			0.502	0.636*

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table reports descriptive statistics of quintile portfolios formed by sorting loadings on equally-weighted common idiosyncratic volatility. CIV loadings are estimated by regressing excess monthly firm-level returns on CIV, controlling for the market excess return factor as in (24). Portfolios are sorted on β_i^{CIV} from the lowest (portfolio 1) to the highest (portfolio 5). The columns Mean and Std.Dev. report equally-weighted average and standard deviation of monthly return within each quintile. The row "5-1" relates to the spread between portfolio 5 and 1. The CIV Loadings column reports the average β_i^{CIV} within each quintile. The Alpha columns refer to the constant term with respect to the CAPM one-factor and Fama-French three-factor model. The asterisks denote the significance level. The sample spans time period from June 1994 to June 2014.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

3.3.3 Robustness to Residual Idiosyncratic Volatility

A possible explanation that higher return being associated with stocks with high CIV loadings is that stocks with large exposure to CIV are also stocks with high idiosyncratic volatilities. In section 3, stocks within higher idiosyncratic quintile are documented with higher average level of return. On the other hand, CIV only accounts for less than 16% of firm-level idiosyncratic volatility.

Table 13 reports portfolios sorted on CIV loadings controlling for firm-level idiosyncratic volatility. The average returns are not strictly increasing within each idiosyncratic volatility quintile. The 5-1 CIV loading return spread increase monotonically from 0.32 to 1.40 along with residual idiosyncratic volatility quintiles. Thus, the CIV effect is more pronounced among stocks with higher idiosyncratic risk. On the other hand, by controlling exposure to CIV, stock returns still reveal strong pattern by idiosyncratic volatilities. The t-statistics of 5-1 idiosyncratic volatility quintiles spread are all above 3. This result validates strong correlation between high idiosyncratic volatility and high return. Nonetheless, CIV only explains a small portion of firm-level idiosyncratic volatility dynamics. In simple words, stocks with high exposure to CIV does not necessarily has high idiosyncratic volatility. One assumption can be that the common movement of idiosyncratic volatilities is driven by business cycles whereas firm-level idiosyncratic volatility are still mainly driven by corporate characteristics.

Table 13: Portfolio sorted by CIV loadings and Residual Idiosyncratic Volatility

	Residual Idiosyncratic Volatility Quintiles						
	1	**2**	**3**	**4**	**5**	**5-1**	**t(5-1)**
1	0.493	0.658	0.547	0.373	2.479	1.986	3.451
2	0.916	1.012	1.193	1.382	3.045	2.129	3.653
3	0.781	1.232	1.543	1.700	3.182	2.400	3.728
4	0.782	1.125	1.388	1.554	3.508	2.726	3.923
5	0.809	1.268	1.459	1.623	3.882	3.074	3.544
5-1	0.316	0.610	0.912	1.251	1.404		
t(5-1)	0.963	1.449	1.773	1.863	1.421		

Note: This table reports equally-weighted average returns sorted on CIV loadings and residual idiosyncratic volatility quintiles. The columns correspond to the CIV loadings dimension. CIV loadings are estimated as constants throughout whole sample period. Idiosyncratic volatility is defined as monthly standard deviation of FF-3 model residuals. Both portfolios are rebalanced monthly. 5-1 reports the spread between portfolio 5 and 1, t(5-1) reports corresponding t-statistics. The sample spans time period from June 1994 to June 2014.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

3.3.4 Robustness to Market Volatility

Table 14: Portfolio sorted by CIV loadings and Market Volatility Loadings

	Market Volatility Beta Quintiles						
	1	**2**	**3**	**4**	**5**	**5-1**	**t(5-1)**
1	1.191	1.379	1.277	0.116	-1.868	-3.059	-2.445
2	1.494	1.409	1.239	1.260	0.170	-1.325	-1.376
3	1.778	1.599	1.416	1.287	1.552	-0.225	-0.342
4	1.561	1.806	1.750	1.478	1.270	-0.291	-0.424
5	2.002	2.223	2.077	2.032	2.135	0.133	0.137
5-1	0.811	0.844	0.800	1.917	4.003		
t(5-1)	0.923	1.095	1.173	2.094	3.037		

Note: This table reports equally-weighted average returns sorted on CIV loadings and residual idiosyncratic volatility quintiles. The columns correspond to the CIV loadings dimension. CIV loadings are estimated as constants throughout whole sample period. Market volatility is estimated as monthly standard deviation of market returns. Market volatility loadings are estimated from implementing regression $R_{it} - Rf_t = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{MV} MV_t + \varepsilon_{it}$. Both portfolios are rebalanced monthly. 5-1 reports the spread between portfolio 5 and 1, t(5-1) reports corresponding t-statistics. The sample spans time period from June 1994 to June 2014.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

Previously CIV is proven to differ from market volatility. This viewpoint is further validated by sorting stocks on CIV loadings and market volatility loadings. Market volatility is defined as the monthly standard deviation of market returns. Analogous to the estimation of CIV loading previously, market volatility loadings are attained from regressing monthly individual excess returns on excess market returns and market volatilities. Thereafter stocks are sorted into five market volatility quintile portfolios. Within each market volatility portfolios, stocks are sorted again by exposure to CIV.

Table 14 reports the equally-weighted average returns by two-way sorting on market volatility betas and CIV betas. Consistent with previous investigations, stocks with high exposure to CIV continues to yield higher returns. Except for the first market volatility beta portfolios, there appears to be monotonically increasing pattern of average returns by CIV betas. The 5-1 spreads on CIV portfolios are mostly significantly positive. Contrariwise, by controlling the exposure to CIV, stocks doesn’t reveal an apparent pattern sorted on market volatilities. The 5-1 spreads on market volatilities quintiles are, however, mostly negative. Therefore, CIV effect on average returns is not entirely driven by market volatility dynamics either.

3.3.5 Robustness to Liquidity Effects

Several papers document relationship between stock returns and liquidity risk. Pastor and Stambaugh (2003) reveal a positive correlation between sensitivity to aggregate liquidity and expected stock returns. Spiegel and Wang (2005) find close intertwinement of stock liquidity and idiosyncratic volatility risk. Highly liquid stocks tend to associate with low level of idiosyncratic volatility. Moreover, they document that idiosyncratic volatility drives out liquidity effects when both factors are used to explain expected return. In this sub-section, Pastor-Stambaugh liquidity series is used as a proxy for market liquidity. Accordingly their liquidity measure is based on individual stocks’ daily volume and market liquidity is computed as equally-weighted average individual volume for every month. The Pastor-Stambaugh non-traded liquidity factor is defined as the innovations in aggregate liquidity (Pastor & Stambaugh, 2003).

Subsequently, the stock sensitivity to Pastor-Stambaugh non-traded liquidity factor is attained from time-series regression controlled for market excess return. Stocks are firstly sorted into five monthly quintile portfolios based on their historical liquidity betas, afterward, stocks are sorted into by CIV betas within each liquidity portfolio.

Table 15 reports the result by controlling Pastor-Stambaugh Liquidity exposure. Average stock return still show increasing pattern along with CIV beta, however not monotonically. The 5-1 CIV loadings spreads still observed to remain positive, ranging from 0.71 per month to 1.30 per month. On the other hand, by controlling CIV exposure, the 5-1 spreads sorted of liquidity betas are mostly negligible. Therefore, liquidity effects cannot account for the spread in average stocks returns from CIV effect. However, by using CIV and liquidity factor simultaneously, CIV drives out the liquidity effect on stock returns. This result coincides with the argument proposed by Spiegel and Wang (2005).

Table 15: Portfolio sorted by CIV loadings and Liquidity Quintiles

	Liquidity Quintiles						
	1	**2**	**3**	**4**	**5**	**5-1**	**t(5-1)**
1	1.025	1.149	0.989	1.254	0.907	-0.118	-0.191
2	1.142	1.348	1.214	1.231	1.376	0.234	0.418
3	1.610	1.317	1.182	1.371	1.548	-0.063	-0.113
4	1.548	1.616	1.356	1.530	1.411	-0.137	-0.224
5	2.331	1.896	2.151	1.965	2.175	-0.156	-0.171
5-1	1.306	0.748	1.162	0.712	1.268		
t(5-1)	1.667	1.170	1.717	1.082	1.638		

Note: This table reports equally-weighted average returns sorted on CIV loadings and liquidity quintiles. The columns correspond to the CIV loadings dimension. CIV loadings are estimated as constants throughout whole sample period. Pastor-Stambaugh liquidity series is used as proxy for market liquidity whereas Pastor-Stambaugh non-traded liquidity factor is defined as the innovations in aggregate liquidity. Liquidity betas are estimated from implementing regression $R_{it} - Rf_t = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{LIQ} LIQ_t + \varepsilon_{it}$. Both portfolios are rebalanced monthly. 5-1 reports the spread between portfolio 5 and 1, t(5-1) reports corresponding t-statistics. The sample spans time period from June 1994 to June 2014.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

3.3.6 Robustness to Momentum Effects

Momentum effect on average stock returns has been widely discussed in the recent literatures. Correspondingly momentum anomaly is defined as the tendency that stocks with high historical return continue to over-perform, and low past return stocks keep falling. Jegadeesh and Titman (1993) document significant positive return by implementing a strategy that long stocks performed well in the past and short opposite category of stocks over three to twelve months holding period.

In order to control momentum effect, stocks are firstly grouped into quintile portfolios by sorting on past 6-month aggregate returns. The holding period is one month. Then within each momentum quintile, stocks are sorted by CIV exposures. Lastly, equally-weighted average returns are calculated for each of the 5×5 portfolios.

Table 16 reports different average returns by CIV betas controlling for momentum. Stocks with the highest exposure to CIV still yield relatively highest level of return on each momentum portfolios. However, the pattern in other CIV portfolios is rather obscure. The lowest average returns appear within the range of first and second CIV portfolios though. Moreover, the 5-1 CIV loadings spreads consistently remain positive. The levels of t-statistics do not differ notably from previous robustness investigations. On the contrary, by controlling CIV exposure, stocks with high past 6-month aggregate returns do not appear to over-perform peer stocks from June 1994 to June 2014.

Table 16: Portfolio sorted by CIV loadings and Momentum Quintiles

	Momentum Quintiles						
	1	2	3	4	5	5-1	t(5-1)
1	0.903	1.114	1.147	1.289	1.494	0.591	0.933
2	1.490	1.441	1.271	1.127	1.486	-0.004	-0.007
3	2.056	1.444	1.342	1.307	1.451	-0.605	-0.986
4	1.811	1.621	1.396	1.373	1.739	-0.072	-0.106
5	2.144	1.604	1.770	1.726	2.505	0.361	0.400
5-1	1.242	0.490	0.623	0.437	1.011		
t(5-1)	1.436	0.771	1.135	0.775	1.481		

Note: This table reports equally-weighted average returns sorted on CIV loadings controlling for past 6-month aggregate return. The holding period for momentum portfolios is one month. The columns correspond to the CIV loadings dimension. CIV loadings are estimated as constants throughout whole sample period. Both portfolios are rebalanced monthly. 5-1 reports the spread between portfolio 5 and 1, t(5-1) reports corresponding t-statistics. The sample spans time period from June 1994 to June 2014.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

To sum up for above subsections of robustness check, neither size, value, residual idiosyncratic volatility, market volatility, liquidity nor momentum effects drives away the spread between portfolio with the highest CIV exposure and one with the lowest CIV exposure.

3.4 Determinants of Common Idiosyncratic Volatility Dynamics

In the previous section, stocks with higher exposure to CIV is found to yield higher average returns. However, the source of CIV dynamic remains uncertain. Duarte et al. (2014) argue that the common component of idiosyncratic volatility can be partially explained by business cycle indicators. Bekaert, Hodrick and Zhang (2012) attempt to use index behavioral variables, corporate variable and business cycle variables to explain the dynamics of aggregate idiosyncratic volatility. Several corporate and business cycle variables found significant at explain aggregate idiosyncratic volatility. Herskovic et al. (2014) argue that common idiosyncratic volatility related to household consumption growth. Earlier figures in this thesis have shown spikes in idiosyncratic volatility trajectories around financial crises, therefore this sub-section investigate the connection of several macroeconomic variables and common idiosyncratic volatility.

Table 17 provides a brief description of all the independent variables being attempted. All the variables are in monthly frequency from June 1994 to June 2014.

Table 17: List of Independent Variables

Variables	Description
UMCSENT	University of Michigan consumer sentiment index
UNRATE	Civilian unemployment rate.
CPI	Consumer price index for all urban consumers.
USRED	NBER based recession indicators for the United States
TERM	Term spread as yield spread between 10-year and 1-year U.S. government bonds.
DEF	Default spread as yield spread between BAA and AAA rated U.S. corporate bonds.
SP500	Standard & Poor's 500 stock market index.
SP500_DIV	Dividend yield on S&P 500 index.
CORR	Average stock return correlation.
SKEW	CBOE SKEW index.
MV	Market return volatility.
VIX	CBOE market volatility index.

Note: This table lists a description and notation of attempted independent variables. All the variables are in monthly frequency.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

The list comprises 11 market and macroeconomic variables, they are used to investigate the contemporaneous relationship with CIV. Specifically, those variables are grouped into three main categories: general economic cycle indexes, financial cycle indicators and market-wide variances. Explicitly, the first variable is the consumer sentiment index, which is an indicator intended to gauge consumer confidence. Unemployment rate is closely related to business cycles, during cycle contractions the rate rises whereas during expansions the rate descends. Consumer price index is used a proxy for inflation, and it is expected to fall during economic contractions. Further, NBER recession indicator is a time series comprises binary variables which indicate business cycle expansion and contractions provided by U.S. National Bureau of Economic Research. A value of 1 is a recession period and a value of 0 is an expansion period.

Term spread has been used as a helpful indicator to predict economic activity, especially in forecasting recessions (Wheelock & Wohar, 2009). Accordingly term spread is defined as the spread between long-term and short-term interest rate. Long-term interest rate can be treated as the future expectation of short-term interest rate whereas the short-term interest rate reveals the current state of economy. Short rates improve while economy improves, if the term spread is largely positive, it indicates future economy is likely to change. Similarly, default spread is also proven to provide useful information regarding economic prospect. Default spread is defined as the difference in rate of return between firms of different credit quality. While term spread reflects anticipation of future prospect of economy, the default spread can be treated more as a proxy for the current state of economy. Investors would demand higher yields for lower-grade bonds during the time of recession especially (Frenkel, Hommel, Dufey, & Rudolf, 2005).

Table 18: Time-series Regression on Common Idiosyncratic Volatility

	I	II	III	IV	V
UMCSENT	-0.012*			0.007*	0.009***
	(-2.56)			(2.06)	(3.51)
UNRATE	-0.231***			0.075***	0.070***
	(-5.66)			(3.44)	(3.74)
CPI	-0.159***			-0.006	
	(-3.86)			(-0.28)	
USRED		0.580***		0.259***	0.256***
		(5.06)		(3.74)	(3.8)
TERM		-0.136***		-0.055*	-0.044*
		(-4.39)		(-2.53)	(-2.17)
DEF		-0.900***		-0.198**	-0.180**
		(-8.79)		(-3.03)	(-3.25)
CORR		-0.298		-3.985***	-3.942***
		(-0.78)		(-13.84)	(-15.50)
SP500		-0.001***		-2E-05	
		(-6.11)		(-0.31)	
SP500_DIV		-0.783***		-0.091	
		(-8.65)		(-1.44)	
SKEW		-0.006		-0.0002	
		(-0.84)		(-0.04)	
MV			0.519***	1.043***	1.064***
			(5.58)	(16.87)	(27.46)
VIX			0.021**	0.001	
			(2.93)	(0.27)	
Constant	5.395***	4.995***	1.586***	1.175	0.779**
	(8.04)	(6.98)	(18.01)	(1.8)	(2.61)
adj. R^2	0.138	0.527	0.534	0.881	0.882

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table reports results from OLS regression of CIV on several market and macroeconomic variables over June 1994 to June 2014. First three columns show regressions on general economic cycle indexes, financial cycle indicators and market-wide variances respectively. The column IV show regression on all the variables. The last column reports variables at least significant at 5% level. Corresponding t-statistics are shown in brackets. Adjusted R-squared for each regression is reported in last row.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

Standard & Poor's 500 index is often considered as one of the best proxies of U.S. stock market cycles, also the dividend yield on S&P 500 index is also included in the analysis. Duarte et al. (2014) document average stock correlation as a significant factor in explaining common idiosyncratic volatility. Moreover, even though CIV is proven differ from the market return volatility, they still share a substantial amount of correlation.

VIX represents an implied market volatility indicator of market's expectation on the stock market volatility over 30 days' horizon in the future. VIX differs from historical volatility because VIX is priced on traded options and forward-looking. Lastly, CBOE skew index is used as a proxy to track the tail risk of S&P 500 index, increasing in skew corresponds to the steepening in VIX curve.

Table 19: Time-series Regression on First Difference of Common Idiosyncratic Volatility

	I	II	III	IV	V
dUNRATE	-0.066			0.142	
	(-0.54)			(1.610)	
dUMCSENT	-0.019***			-0.005	
	(-3.82)			(-1.59)	
dCPI	-0.020			0.021	
	(-0.43)			(0.670)	
USRED		-0.031		0.014	
		(-0.49)		(0.290)	
dTERM		0.043		-0.089	
		(0.430)		(-1.32)	
dDEF		-0.527**		-0.285*	-0.326**
		(-3.28)		(-2.55)	(-3.06)
dCORR		1.228***		-2.035***	-1.938***
		(4.510)		(-7.74)	(-7.45)
dSP500		0.001		0.001*	0.001*
		(0.860)		(2.230)	(2.48)
dSP500_DIV		0.579		0.415	
		(1.460)		(1.520)	
dSKEW		0.01*		0.003	
		(2.200)		(1.070)	
dMV			-0.520***	-0.754***	-0.746***
			(-14)	(-15.95)	(-17.16)
dVIX			-0.005	-0.002	
			(-1.39)	(-0.39)	
Constant	-0.004	-0.003	-0.003	-0.010	-0.006
	(-0.20)	(-0.13)	(-0.23)	(-0.69)	(-0.47)
adj. R^2	0.047	0.165	0.505	0.633	0.623

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table reports results from OLS regression of first-difference of CIV on first-differences of several market and macroeconomic variables over June 1994 to June 2014. NBER recession indicator is untransformed. First three columns show regressions on general economic cycle indexes, financial cycle indicators and market-wide variances respectively. The column IV show regression on all the variables. The last column reports variables at least significant at 5% level. Corresponding t-statistics are shown in brackets. Adjusted R-squared for each regression is reported in last row.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

Several time-series regressions of CIV is implemented on above mentioned variables in order to determine which variables capture the dynamics of CIV. Table 18 reports the regression output. In the first column, general macroeconomic indicators explain 12.6% of a total variation in CIV. In comparison, financial business cycles indicators and market-wide volatility series explain 52.7% and 53.4% of a total variation respectively. Furthermore, in column IV, a regression using all the independent variables is implemented. However this regression is accompanied with highly multicollinearity, therefore many insignificant variables are observed. Subsequently in the last column, only significant variables from the previous regression are retained in the model. The significant variables comprise consumer confidence index, unemployment rate, NBER recession index, term spread, default spread, average stock correlation and market return volatility. The resulting adjusted-R-squared is 88.2%. Unsurprisingly market volatility and average return correlation appear to be the main driving force of CIV dynamics. In addition, other business cycle indicators play a vital role in explaining CIV variations. For example, CIV is positively correlated with NBER recession indicator, this suggests that market uncertainty tends to rise at recession time, and increasing market uncertainty drives up the level of CIV. Furthermore, default spread is negatively correlated with CIV, this is particularly surprising result because it infer lower CIV at bad economic times. The average stock correlation is also negatively correlated with CIV, which suggests lower average idiosyncratic volatility level when stocks contain a larger portion of co-movement. Nevertheless, the regression provides robust evidence that firm-level idiosyncratic volatilities comprise a common component affected by economic condition.

Furthermore, Table 19 studies the underlying dynamics of the change in CIV. Analogous regression is implemented on the first difference of underlying factors. The NBER recession indicator remains untransformed as it is a binary variable indicator. On the contrary to the impressive result from regressions on the levels of CIV, the regression on the first-changes of CIV exhibits much poorer goodness of fit. Only the difference in default spread, difference in average return correlation and difference in market volatility remain significant at 5% level. The difference in S&P 500 index adds as a new significant explanatory variable, however the coefficient is negligible. Noticeably, financial cycle indicators have a low-level of explaining power in column II.

To briefly sum up, the level of common idiosyncratic volatility is found to be significantly correlated with the macro business cycle proxies. However, the changes in CIV is less correlated with the selected factors.

3.5 The Price of Common Idiosyncratic Volatility

Previous sections revealed that firstly stocks with high CIV exposure yield higher average return from June 1994 to June 2014, as well as CIV, can be partially represented by business cycle indicators. In the last section, the effectiveness of CIV as a systemic pricing factor is investigated. If CIV is a missing systemic variable, then it should be able to help explaining cross-sectional stock returns. Fama-French 25 size-B/M portfolios and Fama-French 30 industry portfolios are used to investigate the asset pricing implication of CIV in cross-sectional returns. Subsequently, Fama-Macbeth two-step procedure is adapted to measure the risk premium on CIV. In the first step, a time-series regression is performed to obtain portfolios' loadings on each factor. In the next step, a cross-sectional regression of all portfolios returns is implemented against all the estimated loadings in order to compute the risk premium (Cochrane, 2005). The initial model is an augmentation of FF-3 factor model:

$$r_{it} = c+\beta_i^{MKT}\lambda_{MKT}+\beta_i^{SMB}\lambda_{SMB}+\beta_i^{HML}\lambda_{HML}+\beta_i^{CIV}\lambda_{CIV}+\varepsilon_{it} \quad (26)$$

Table 20 reports the estimates by using 25 size-B/M portfolios. This is a replication of the asset pricing test used by (Ang, Hodrick, Xing, & Zhang, 2006). They formed this estimation based on size-B/M portfolios to evaluate the explanatory power of the volatility index. The CIV coefficient yields in this table significantly positive results.

Table 20: Estimation of CIV premium using 25 size-B/M portfolios

	I	**II**	**III**	**IV**
MKTRF	1.004***	1.009***	1.018***	0.993***
	(69.130)	(71.280)	(74.690)	(83.780)
SMB	0.506***	0.506***	0.514***	0.509***
	(5.200)	(5.200)	(5.530)	(5.220)
HML	0.355***	0.359***	0.337***	0.350***
	(4.230)	(4.260)	(4.560)	(4.140)
CIV		0.169***	0.152***	0.198***
		(4.390)	(4.210)	(3.760)
RMW			0.031	
			(0.630)	
CMA			0.032	
			(1.150)	
MOM				-0.0296**
				(-3.42)
LIQ				1.386**
				(3.490)
Constant	0.011	-0.428***	-0.409***	-0.453**
	(0.290)	(-4.56)	(-4.42)	(-3.60)
R^2	0.752	0.752	0.753	0.752

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table reports factor premiums on 25 size-B/M portfolios by implementing Fama-Macbeth two-step procedure. MktRF is the excessive return on the market portfolio, SMB and HML are the Fama-French size and value factors. RMW and CMA are the Fama-French profitability and investment factors. MOM is the momentum factor and LIQ is Pastor & Stambaugh aggregate liquidity measure. Corresponding t-statistics are shown in brackets. Average R-squared for each regression is reported in last row.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

However, (Duarte, Kamara, Siegel, & Sun, 2014) challenged the use of size-B/M portfolios in estimation by arguing that the strong factor structure of such portfolios can introduce the risk of spurious result. Therefore, as a replication, Table 21 provides an output from analogous procedure by using 30 industry portfolios. The factor premium on CIV remains positive, however the significance drops. By including additional factors, coefficient on CIV turns insignificant. The size factor also yields insignificant loading. To summarize, CIV adds some explanatory power to stock returns. However, the improvement of the augmented pricing model is still trivial. Thus, the robustness of CIV in pricing stock return cannot be affirmed.

Table 21: Estimation of CIV premium using 30 industry portfolios

	I	II	III	IV
MKTRF	1.011***	1.016***	1.062***	0.984***
	(19.54)	(19.24)	(23.23)	(20.08)
SMB	0.0697	0.0698	0.140**	0.0804
	(1.53)	(1.54)	(2.93)	(1.71)
HML	0.351***	0.354***	0.265**	0.338***
	(4.85)	(4.88)	(3.56)	(4.7)
CIV		0.140*	0.0733	0.0782
		(2.31)	(1.01)	(1.09)
RMW			0.224**	
			(3.39)	
CMA			0.0736	
			(1.22)	
MOM				-0.0590*
				(-2.08)
LIQ				1.807
				(1.54)
Constant	0.0134	-0.361*	-0.312	-0.14
	(0.2)	(-2.04)	(-1.63)	(-0.74)
R^2	0.467	0.467	0.471	0.469

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table reports factor premiums on 30 industry portfolios by implementing Fama-Macbeth two-step procedure. Corresponding t-statistics are shown in brackets. Average R-squared for each regression is reported in last row.

Source: Bloomberg (2014) & Kenneth R. French Data Library (2014)

CONCLUSION

This thesis aimed to study the behavior of idiosyncratic return volatilities in NYSE, AMEX and NASDAQ from 1994 to 2014. The firm-specific idiosyncratic residual is estimated from Fama-French 3-factor model, and the monthly idiosyncratic volatility is computed as the average squared idiosyncratic residual. Firstly, stocks with high idiosyncratic volatility are found to yield a higher return than stocks with low idiosyncratic volatility.

The main results of this thesis are as follows.

First, by using a cross-sectional comparison, a significant common pattern is found in size, value and industry portfolios. This phenomenon is further validated by calculating the average pairwise correlation between total returns, FF3 residuals and idiosyncratic volatilities respectively. Fama-French three factors appears to absorb the systematic variation in stock returns. However, it has little effect on absorbing volatility commonality.

This differs volatility variation from return variation. Moreover, instead of being consistently high over time, commonality in idiosyncratic volatilities appears to be volatile. A figure suggests that the commonality in idiosyncratic volatilities might be higher at the time of market turmoil. However, the co-movement remains at a low level in several years.

Second, firm-level idiosyncratic volatility accounts for the greatest share of firm-level total return volatility. Common idiosyncratic volatility is calculated as the equally-weighted average of firm-specific monthly idiosyncratic volatilities. This common component explains 14% of idiosyncratic volatility variations, by removing the common component, firm-level idiosyncratic volatilities are observed to exhibit a lower level of co-movement. Moreover, despite their similarity, common idiosyncratic volatility is still different from market volatility.

Third, stocks with the highest sensitivity to common idiosyncratic volatility always yield higher returns than the stocks with the lowest sensitivity to CIV. This pattern is found to be robust and consistent, however, not significant in some case.

Fourth, the level of common idiosyncratic volatility is observed to be correlated with several macroeconomic proxies, in particular to the default spread, average stock return correlation and market return volatility. On the other hand, this pattern seems to be less significant with the changes in idiosyncratic volatility. Therefore, the correlations partially support the observation that commonality in idiosyncratic volatility is higher in financial distress.

Finally, the asset pricing implication of CIV is examined using Fama-Macbeth estimation method. However, no significant improvement is documented by augmenting Fama-French 3 factor model with CIV.

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APPENDIXES

LIST OF APPENDIXES

Povzetek

Vloga idiosinkratične volatilnosti pri vplivu na delniška vračila je v zadnjem času dobila veliko pozornosti. Kljub temu pa je le nekaj objavljenih člankov raziskalo dinamiko skupnega gibanja idiosinkratične volatilnosti na nivoju podjetja. To diplomsko delo je posvečeno temu, da razišče sistematične lastnosti znotraj podjetno specifične idiosinkratične volatilnosti z uporabo podatkov iz NYSE, AMEX in NASDAQ od leta 1994 do 2014. Najprej se je z analizo preostankov modela »Fama-French three factor« izkazalo, da je model nezmožen absorbirati afinitete v delniški volatilnosti kljub njegovi zmožnosti, da absorbira variacije v delniških vračilih. Za presečne idiosinkratične volatilnosti se je izkazalo, da sledijo skupnemu vzorcu. Kakor koli, nivo afinitete sčasoma ni več konsistenten, temveč precej fluktuira s stanjem gospodarstva. Nadalje, z odpravo skupne idiosinkratične volatilnosti (»common idiosyncratic volatility – CIV«), so idiosinkratične volatilnosti na nivoju podjetja znatno znižale povprečno parno korelacijo. Poleg tega so delnice z najvišjo dovzetnostjo na skupno idiosinkratično volatilnost prinesle višje vračilo kot delnice z nižjo dovzetnostjo na skupno idiosinkratično volatilnost. Vendarle pa ni bilo dovolj dokazov najdenih v podporo skupne idiosinkratične volatilnosti kot cenitvenega faktorja. Končno, ugotovljeno je bilo, da ima skupna idiosinkratična volatilnost vzorec, ki je v povezavi z več zastopniki finančnega cikla.

Summary in English

The role of idiosyncratic volatility in affecting stock returns have obtained a great amount of attention lately. However, only a few published papers investigated the dynamics of co-movement of firm-level idiosyncratic volatility. This thesis is committed to exploring the systematic property within firm-specific idiosyncratic volatilities by using the data in NYSE, AMEX and NASDAQ from 1994 to 2014. Firstly, by analyzing the residuals from the Fama-French 3-factor model, the model is found to be unable to absorb the commonality in stock volatilities, despite its ability to absorb the systematic variation in stock returns. Cross-sectional idiosyncratic volatilities are found to follow a common pattern. However, the level of commonality is not consistent over time, but rather fluctuates with the state of economy. Further, by removing common idiosyncratic volatility (CIV), firm-level idiosyncratic volatilities are observed to have significantly lower average pairwise correlation. Moreover, stocks with highest sensitivity to CIV are observed to yield higher returns than the stocks with lower sensitivity to CIV. However, not enough evidence is found to support CIV as a pricing factor. Finally, CIV is found to have a pattern being correlated with several financial cycle proxies.