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EXPLORATIONS INTO IDIOSYNCRATIC RISK

By

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ABSTRACT

EXPLORATIONS INTO IDIOSYNCRATIC RISK

By

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Following a study by Campbell, Lettau, Malkiel, and Xu (2001), which documents an upward trend in idiosyncratic volatility that lasted for nearly for decades, not only the interest in idiosyncratic risk has been renewed, but it became a highly researched topic in finance literature. Numerous papers propose explanations of the dynamics of idiosyncratic volatility or consider its consequences and implications. We choose to look at the behavior of idiosyncratic risk from three different perspectives reflected in the three essays, which comprise this dissertation.

The first essay proposes an explanation of the observed empirical patterns in the average idiosyncratic volatility initially documented by Campbell, Lettau, Malkiel, and Xu (2001). In particular we show that idiosyncratic volatility is driven (at least in part) by market value concentration. In a more concentrated market, it is easier to forecast movements in the aggregate market index, and hence, the relative usefulness of analysis that relate individual stock price movements to aggregate market movements (i.e., the Market Model) is greater. Investors will therefore place greater emphasis on such analysis in more concentrated markets, which will exhibit less idiosyncratic volatility than markets in which value weights are more closely centered around $\frac{1}{n}$. Our empirical analysis suggests that the two variables are cointegrated and that a larger dispersion of market capitalization weights results in higher idiosyncratic volatility.

The second essay provides a firm-by-firm estimation of trends in idiosyncratic volatility. By doing so we can identify the following sources that contribute to the

trend in the market average idiosyncratic risk (Campbell, Lettau, Malkiel, and Xu (2001)): new issues, delistings, and existing firms with positive, negative, or no volatility trends. This identification is crucial because the relative importance of each source has drastically different investment implications. Unlike the current literature, we show that many firms experience positive or negative volatility trends, and their dynamic combination leads to increases or decreases in the market average idiosyncratic risk. Our approach of firm-by-firm estimation of trends further allows us to pinpoint the factors that are behind the fluctuations in idiosyncratic risk and examine the relative importance of existing interpretations including (1) firm fundamentals (Wei and Zhang (2006) and Irvine and Pontiff (2005)), (2) institutional ownership (Malkiel and Xu (2003)), and (3) speculative trading (Brandt, Brav, and Graham (2005)).

Several authors proposed that growing institutional ownership share can explain the idiosyncratic risk puzzle (Malkiel and Xu (2003), Dennis and Strickland (2005)). In the third essay we argue that the causality in this relationship may run in the opposite direction as well, i.e. when changes in idiosyncratic risk induce changes in institutional ownership. This assertion is consistent with Merton (1987) limited information model, which predicts that investors are forced to hold (part of) idiosyncratic volatility in their portfolios. Provided that institutions have better abilities to diversify then non-institutional investors, companies with growing idiosyncratic risk also have increasing share of institutional owners. Therefore, observed trend in average idiosyncratic volatility in the U.S. financial market can be a reason of increasing institutional ownership share. Our causality tests in VECM specification support this hypothesis.

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CHAPTER 1

Structure of Idiosyncratic Risk: An Insight into Market Model Error

1.1 Introduction

Finance factor models, though intuitively appealing, often perform poorly when confronted with the economic data (see, for example, Banz (1981), Bhandari (1988), Stattman (1980), Fama and French (1992)).[1] For instance, Roll (1988) poses the following question: how well do the various factors proposed by theory explain the realized changes in securities prices when the factors are tested on U.S. data? The answer is quite disappointing. At best, only one-third of the ex-post observed returns can be accounted for by the major known factors, or in other words, the model R-squared is quite small, leaving a significant part of the return in the form of an unexplained error. Similar patterns hold internationally (see Morck, Yeung, and Yu (2000)).

Additional intriguing evidence regarding Market Model error appears in Campbell,

[1]By "factor models" we refer to those that employ market-wide factors to explain stock returns. They include such models as the Arbitrage Pricing Theory (APT), Capital Asset Pricing Model (CAPM), or multivariate CAPM. The empirical representation of these models in terms of realized returns is referred to as the "Market Model". Note, however, that our analysis applies only to those models that include the market index along with other factors.

Lettau, Malkiel, and Xu (2001) (henceforth, CLMX). CLMX find that the variance of the model residual steadily increased over the last four decades (although Brandt, Brav, and Graham (2005) report it fell abruptly after 2000). Thus, not only is a large portion of returns unexplained, but the error has a distinct time-series structure. Morck, Yeung, and Yu (2000) present evidence on the cross-sectional correlation between a country's average idiosyncratic volatility and level of GDP. They are unable to explain this relationship by the fundamentals.

The above discussion suggests that factor models fail to account for a certain phenomenon present in the market. Some insight into the nature of this phenomenon can be gained by looking at the structure of market model error. The purpose of the present study is to provide theoretical justification for the existence of a non-random, non-Gaussian error in the market model and to identify the economic forces behind it. Based upon the evidence in Campbell, Lettau, Malkiel, and Xu (2001), we are concerned with those variables that are able to explain the behavior of market model error variance.[2]

In this study we make several simplifying assumptions regarding investors' behavior. Our primary interest lies in the outcomes of this behavior (as reflected in realized returns), not in its motives. This means we consider assumptions suitable for modeling purposes as long as they are useful in explaining behavioral outcomes even if the agents themselves believe they follow a different strategy from the one we use in our investigation.

We start by assuming that investors rely on the Market Model in security evalu-

[2]Note that the primary focus of this investigation is average idiosyncratic risk (or average return correlations) in the economy. This is not the same as average return dispersion. For instance, a large return dispersion over a specific time period may imply either near-zero or high negative return correlations. If all returns are moving in perfect unison they could be either very dispersed or very concentrated. Of course, some information about return variation can still be supplied by the return dispersion as discussed in Connolly and Stivers (2006).

ation.[3] The attractiveness of factor models lies in the simplicity of their application. Specifically, one does not need to know all available information about cross-return correlations in order to price a security; rather, it is enough to know how the security's price varies with respect to a market-wide index (or factor portfolios). The idea is that it is reasonable for investors to complement information about one stock by their knowledge about the market as a whole and its influence over the security. For instance, investors may use the market index and the one-factor model to gain additional insight.

The problem with factor models such as the CAPM is that they assume investors optimize their portfolios using data on returns distributions. This in turn implies that the resulting market portfolio is efficient. In this case it becomes optimal for all investors to use the factor model along with the market portfolio in security evaluation instead of using (costly to collect) information about returns distributions. But this contradicts the initial assumption the CAPM makes, rendering the market portfolio possibly inefficient. How can the equilibrium be sustained in this situation?

It is also worth pointing out that using the market portfolio in security analysis is not as straightforward as it may seem. First, it is hard to measure such a portfolio (Roll (1977)). Further, there are errors in the model equation, which can render the evaluation results imperfect or incorrect. Distribution analysis cannot, therefore, be completely discarded. Indeed, the latter is superior (in accuracy) to the Market Model if the distribution characteristics were fully observable. Since this is not the case, however, distribution analysis is also imperfect. In this paper we consider the case in which investors combine the two approaches to make a more efficient evaluation of security returns.

Consider the following example of how the information in the market index can be used in the analysis of returns. Imagine an investor who knows little about stock

[3]Some survey studies indicate that factor models are actually used quite often by corporate managers in the analysis of the cost of capital; see, for instance, Gitman and Vandenberg (2000).

A. We want to determine the best prediction about the return on this security if the investor knows that on average the returns on the market will increase. Most likely, the investor would think that the return on A will increase as well. Assume that market index behavior is more forecastable (with respect to accuracy and effort) if much of its value is concentrated in fewer stocks (market leaders). Such concentration increases the effectiveness of the factor models as predictors of an individual stock's return relative to other sources of information (such as analysts' forecasts or individually collected information on the company). Thus. if a significant proportion of investors expect a stock to behave in a certain way, its price will adjust in equilibrium accordingly.

The existence of market favorites, i.e., firms that have attracted a majority of investors' attention, is suggested by the fact that the 30 stocks of the Dow Jones Industrial Index are often referred to as "the market". This argument has even more appeal if we take into account the fact that "the market" actually consists of several thousands of stocks and the Dow accounts for only one-fifth of its value. Much broader indexes are available (e.g., Wilshire 5000, NYSE Composite or NASDAQ Composite), but they are not as popular with investors. Beneish and Gardner (1995) show that the Dow stocks are more widely followed by analysts and hence have more available information than other companies. Also, as Merton (1987) suggests, each investor confines his attention to a small portion of the universe of available securities. What happens, however, to those stocks that are not as widely followed? We suggest that their future returns are evaluated (at least in part) based on the evaluations of the major market players.

We assume that the market index's predictability depends on the influence of its major constituent stocks and therefore on market concentration. But the concentration can be affected by the new companies in the market in addition to changes in the relative value of existing companies. While an increasing number of securities may be expected to increase the effect of the law of large numbers on the accuracy of evaluation (assuming the securities are independent). we do not consider this effect here. The total number of stocks in the market increased from about 2000 to 7000 during the period under analysis. However, the effect of the law of large numbers fully applies to a sample of between 50 and 70 stocks, after which point increasing the sample size does not make much of a difference. Admittedly, though, in the case of only a few securities, the overall evaluation effect can be non-linear or otherwise different from our analysis.

Investors' partial reliance on the market index is not irrational given that collecting and processing information is costly, that is, it is an efficient way to deal with information constraints. First, use of the market index reduces investor-specific costs of collecting information (minus, of course, losses due to reduced forecast accuracy). Second, investors can share the costs for market index analysis, since large securities are widely followed by the press (information spillover effect). Finally, the well developed CAPM, which relates the market as a whole and its individual components, can be efficiently used as an aid in security evaluation.

One may be inclined to think that the above arguments should only reinforce the validity of the Market Model. But this is not necessarily the case. For example, the traditional CAPM derives implications of investors choosing stock prices given the distributions and correlations of the underlying cash flows. The model does not account for the fact that investors may be using the CAPM itself to price individual stocks.[4] This imposes limits on the model's explanatory power and implies a particular structure for its error. This structure can be linked to the relative concentration of market value in the economy because a higher dispersion of value limits the ability of investors to rely on the market index and the factor models. If the market consists of

[4]This does not necessarily imply endogeneity of the model, though it does imply, as we will see later, that the variance of the market index is related to the model error. That said, the index and the error can still be uncorrelated, and the regular model still holds in terms of expectations.

a few large and many small companies (i.e., concentrated), the large stocks are used to predict the behavior of the small, generating correlations across securities that are over and above the correlations based upon their fundamentals.

For example, consider a market that consists of two companies, A and B, which use the same supplier of raw materials. Because their performance, and therefore stock returns, are linked to the performance of this supplier, the part of their returns that are determined by fundamentals (e.g., earnings) is correlated. Suppose now that A is a big company and is considered by investors to be a market index measure, whereas B is a small company. Investors will pay close attention to A's performance, evaluating its stock based on collected information. In contrast, due to the costs of collecting information, B will not be researched as intensively, in which case the agents will price stock B (in part) according to the expectation that its return follows the return of the large company, which in turn will increase correlation between the returns of A and B. In a dispersed market, on the other hand, every stock is its own trend-setter, and the relative gain of relying on the market index as opposed to gathering firm-specific information is small. The Market Model residual behaves more like a random Gaussian error in this case, as is usually expected.

We introduce a new variable, the "Quasi-Herfindahl Index" (γ_t), which measures market value concentration and captures the ability of investors to rely on a market-wide index. Our empirical tests show that γ_t accounts for part of the observed Market Model error variance fluctuations for various measures of idiosyncratic risk. The results suggest that lower market value concentration increases idiosyncratic risk. Additionally we find that γ_t is unrelated to several other market-wide variables with the capability of explaining fluctuations in idiosyncratic volatility (e.g., the total number of securities on the market and the idiosyncratic volatility of fundamentals).

The idea that concentration may be related to stock returns has also been recently explored in the literature. Specifically, Hou and Robinson (2006) suggest that concentration is inversely related to risk. This relationship arises if firms in highly concentrated industries are insulated from distress risk or are under lower pressure to engage in risky innovations. Alternatively, our explanation of this relationship is based on investors' evaluation of security returns.[5]

Our findings have several implications. First, it immediately follows that Market Model error variance is non-Gaussian and that it is related to an economy-wide variable. This means that statistical methods other than the least squares regression may better estimate the model. For instance, modeling the error variance in a certain framework may be desirable in empirical research. The results also emphasize the importance of idiosyncratic variance as an indicator of investors' knowledge about future returns, as discussed by Durnev, Morck, Yeung, and Zarowin (2003). Finally, this paper advocates the existence of an additional link between idiosyncratic variance and level of information about return distributions available to investors: consistent with the literature, it suggests that a higher Market Model error variance implies more informative prices.[6]

The remainder of the paper is structured as follows. Section 2 summarizes the relevant literature. Theoretical derivations are presented in Section 3. Section 4 describes empirical testing methods, data, and results. Finally, conclusions and possible extensions are discussed in Section 5.

[5]A concern may arise with respect to the relationship between concentration and average idiosyncratic risk, in view of the recent evidence that suggests idiosyncratic risk and liquidity are negatively correlated in the cross-section of securities (see Spiegel and Wang (2006)). If small stocks are less liquid and are the source of an increase in average market liquidity, liquidity and concentration may be related, which would translate into a relationship between concentration and idiosyncratic risk. We argue that this is not likely to be the case, however, since smaller stocks are allowed to be in the market as long as they provide sufficient liquidity. In other words, adding small securities to the market does not necessarily change the average liquidity level and hence the liquidity does not need to be related to the market value concentration.

[6]This paper is also related to cross-sectional studies of the average idiosyncratic risk in the economy and its link to Gross Domestic Product (see Morck, Yeung, and Yu (2000), Jin and Myers (2004)). It is not the purpose of this study to investigate the connection between a country's level of development and its information efficiency. But if we assume that investors are better aware of return distributions in more advanced economies, such countries should have a higher average idiosyncratic risk, as found in the literature.

1.2 Relevant literature

Campbell, Lettau, Malkiel, and Xu (2001), Campbell and Lettau (1999), Morck, Yeung, and Yu (2000), Malkiel and Xu (1999) and Billio and Pelizzon (2003), among others, document empirical regularities in the behavior of idiosyncratic risk. These papers indicate that on average idiosyncratic volatility has increased over time in various industries and countries, moving in the direction opposite that of the business cycle and recording lower values in less developed economies. In contrast, Hamao, Mei, and Xu (2003) find that idiosyncratic risk is *pro-cyclical* in Japan. They attribute this puzzling evidence to the uniqueness of the Japanese market, where most firms are members of business groups, which increases the correlation of their fundamentals and as a result the correlation of their returns.

Campbell, Lettau, Malkiel, and Xu (2001) suggest several factors that can potentially account for their findings: conglomerate breakups, early IPOs, executive stock option compensation, emerging new markets for derivative instruments, more volatile betas, and higher institutional ownership. With respect to conglomerates, they argue that such firms are themselves diversified portfolios of various production units, all combined into one stock. When split into several companies, a number of stocks are created, each with its own price, decreasing average correlation of stock prices on the market. Similarly, Campbell, Lettau, Malkiel, and Xu (2001) argue that early IPO's can also increase average estimated firm-specific risk. Their rationale is that firms issue equity early in life, when their fundamentals are highly volatile, and the volatility of fundamentals translates into a higher volatility of equity returns.

Executive stock option compensation, which has grown in popularity over time, may also induce higher return volatility. The argument is based on the fact that owners of stock options benefit from increases in the underlying stock volatility. Managers therefore may be inclined to choose projects that are likely to increase stock price fluctuations. To the extent that more managers own stock options, the average volatility of stock returns is higher. Turning to emerging new derivative markets, Campbell, Lettau, Malkiel, and Xu (2001) posit that in principle, they can also increase volatility of returns by reducing the information content of stock prices. This would happen, for instance, when the introduction of a new derivative market encourages trading by informed speculators, as less informative stock prices result in more volatile returns. Next, higher volatility of betas are argued to affect the volatility of stock prices and hence returns via the effect on the discount rates. Finally, institutional owners, whose judgment is relatively homogeneous and who possibly rely on only a few common factors, may be responsible for an increase in the average firm-specific risk. The evidence suggests that the share of institutional investors' holdings has grown at the same time the average idiosyncratic volatility of returns has increased.

Some of the more recent findings in the literature support these predictions. Cohen, Hall, and Viceira (2000) find a positive relationship between executive option holdings and a firm's idiosyncratic risk. Malkiel and Xu (1999) demonstrate that institutional ownership is able to forecast stock volatility for industry portfolios. And Morck, Yeung, and Yu (2000) suggest that increased reliance on external financing, which implies more securities are present in the market, may be able to explain the increase in the average idiosyncratic volatility.

A number of studies propose additional explanations for increased return volatility. For instance, Schwert (2001), Agrawal, Bharath, and Viswanathan (2004), and Mazzucato (2002) show that higher demand uncertainty translates into higher equity volatility. Malkiel and Xu (2003) attribute the trend in average idiosyncratic risk to an increase in institutional ownership and expected earnings growth, and they confirm earlier evidence that exclusion of NASDAQ firms from the sample reduces the magnitude of the observed trends.

Jin and Myers (2004) relate the trend in return volatility to the opaqueness of firms to outside investors, asserting that less transparent companies, which have both informed and uninformed equity holders, have a larger volatility of stock returns. Fama and French (2004) suggest that the rise in idiosyncratic risk in the U.S. market can be partly explained by an increased dispersion of profitability among the new lists. Pastor and Veronesi (2003) also point out that economic fundamentals (i.e., volatility of profitability) can account for empirical regularities in idiosyncratic risk. Additionally, they propose that the market learns about a firm's behavior over time, since younger firms have higher stock volatility than older companies. The relationship between idiosyncratic volatility and firm maturity is also explored by Fink, Fink, Grullon, and Weston (2005), who argue that changes in the market's average idiosyncratic risk are solely attributed to the influence of newly listed securities, which exhibit high firm-specific return variation.

Irvine and Pontiff (2005) are able to explain the trend by an increase in idiosyncratic volatility of sales, earnings, and cash flows, while Wei and Zhang (2006) claim that the downward trend in returns on equity combined with an upward trend in its volatility resolves the puzzle. Rajgopal and Venkatachalam (2007) attribute the trend to the decreased quality of earnings reports and as a result an increase in the dispersion of analysts' forecasts, which in turn may translate into a higher average idiosyncratic risk. Guo and Savickas (2007) propose the surge in the number of publicly traded companies as a likely explanation. Finally, Brandt, Brav, and Graham (2005) suggest that periods of large idiosyncratic variance mark episodes of a rise in speculation in financial markets.

1.3 Structure of Market Model error variance

In the previous section we describe several of the numerous factors that appear to be related (intuitively and empirically) to the behavior of Market Model error variance. The fact that so many relevant factors exist suggests that these studies may only be proof that in an economy, "everything is related to everything". The following derivations provide a theoretically justified structure for the changes in idiosyncratic volatility. The CAPM error decomposition in this section is based on several assumptions about investors' forecasting and uncertainty about the returns distributions. The goal is to determine how this uncertainty and investors' reliance on the Market Model (to resolve it) affects the observed error of the original model.

In the model of asset prices derived by Sharpe (1964) and Lintner (1965), investors are assumed to know the expected value of discounted future cash flows and their covariance structure. Using this knowledge and portfolio diversification principles they evaluate the present value of individual stocks. The current prices of securities adjust to reflect investors' evaluation so that the following relationship holds in equilibrium:

$$E(r_i) = \beta_i E(r_m), \tag{1.1}$$

where r_i is the (excess) return on stock i, r_m is the (excess) return on the market index, and $\beta_i = \frac{cov(r_i,r_m)}{var(r_m)}$. Since at any given moment actual returns are not equal to their mean values, this relationship yields (mean zero) errors (e_{it} and e_{mt}), given as follows:

$$r_{it} = E(r_i) + e_{it}, \tag{1.2}$$

$$r_{mt} = E(r_m) + e_{mt}, \tag{1.3}$$

and

$$r_{it} = \beta_i r_{mt} + (e_{it} - \beta_i e_{mt}) = \beta_i r_{mt} + \eta_{it}, \tag{1.4}$$

where $\eta_{it} = e_{it} - \beta_i e_{mt}$.

Assume that based on individually collected information about security i each investor k makes her evaluation of return i, $E(r_i) + \nu_{it}^k$, where ν_{it}^k is evaluation error (idiosyncratic information source). Each investor is assumed to have a different evaluation error, but on average these errors are zero ($E(\nu_{it}^k) = 0$) across investors and across time. Also assume for simplicity that all evaluation errors have the same variance (level of uncertainty in the economy). So far the above assumptions do not change the nature of the Market Model relationship, which still holds in terms of the averages (Lintner (1965)). Additionally, assume that an investor can use her evaluation of the market index, $r_{mt} + \nu_{mt}^k$, and the beta to evaluate individual securities (ν_{mt}^k is the evaluation error, similar to ν_{it}^k, and the two are assumed to be uncorrelated). These two pieces of information can be combined to form investor k's evaluation of a security return as follows:

$$r_{it}^k = \alpha_i^k(E(r_i) + \nu_{it}^k) + (1 - \alpha_i^k)\beta_i(r_{mt} + \nu_{mt}^k) \tag{1.5}$$

$$\begin{aligned}
&= \alpha_i^k(E(r_i) + \nu_{it}^k) + (1 - \alpha_i^k)(r_{it} - \eta_{it} + \beta_i \nu_{mt}^k) \\
&= \alpha_i^k(E(r_i) + \nu_{it}^k) + (1 - \alpha_i^k)(E(r_i) + \beta_i e_{mt} + \beta_i \nu_{mt}^k) \\
&= E(r_i) + \alpha_i^k \nu_{it}^k + (1 - \alpha_i^k)\beta_i(e_{mt} + \nu_{mt}^k).
\end{aligned}$$

The expected value of this forecast is $E(r_i)$ and its mean squared error (assuming no correlation between ν_{it}^k and e_{mt}[7]) is $\alpha_i^2\sigma_{\nu i}^2 + (1 - \alpha_i)^2\beta_i^2(\sigma_m^2 + \sigma_{\nu m}^2)$, where $\sigma_{\nu i}^2 = var(\nu_{it}^k)$, $\sigma_{\nu m}^2 = var(\nu_{mt}^k)$, and $\sigma_m^2 = var(e_{mt})$. Minimizing this expression with respect to α_i^k gives:[8]

$$\alpha_i^k = \frac{\beta_i^2(\sigma_m^2 + \sigma_{\nu m}^2)}{\sigma_{\nu i}^2 + \beta_i^2(\sigma_m^2 + \sigma_{\nu m}^2)} = \frac{\beta_i^2}{\frac{\sigma_{\nu i}^2}{\sigma_m^2 + \sigma_{\nu m}^2} + \beta_i^2} = \alpha_i. \tag{1.6}$$

In the above expression all investors arrive at the same alpha for stock i because we assumed that investors have equal abilities of collecting information about returns and the market index, i.e. $\sigma_{\nu i}^2$ and $\sigma_{\nu m}^2$ are the same across investors. If we allow

[7]This assumption implies that the mean evaluation error is not related to the deviations of r_{mt} around its mean value.

[8]The main result will follow as well if we minimize some concave function of this expression instead of the mean squared error. Such function can be chosen based on the assumed utility of the agents.

these variances to change over time, equation (1.6) becomes:

$$\alpha_{it} = \frac{\beta_i^2}{\frac{\sigma_{\nu it}^2}{\sigma_{mt}^2+\sigma_{\nu mt}^2} + \beta_i^2}. \tag{1.7}$$

The above assumptions add another dimension to the model (or to the model error[9]). As we can see from equation (1.7), the magnitude of α_{it} depends on the ratio of the error variances, which gives the relative advantage of using the market index information versus the stock-specific information to evaluate the returns.

Assume further that the observed returns on the market are the average return evaluations across agents plus an error term:[10]

$$r_{it} = \frac{1}{K}\sum_k r_{it}^k + \delta_{it} = \alpha_{it}E(r_i) + (1-\alpha_{it})\beta_i r_{mt} + \delta_{it} + \alpha_{it}\frac{1}{K}\sum_k \nu_{it}^k + (1-\alpha_{it})\frac{1}{K}\sum_k \nu_{mt}^k. \tag{1.8}$$

Given that evaluation errors are zero on average, the last two terms are negligible for large K (number of investors), therefore, we ignore them in the remaining derivations. The above equation can be rewritten as:

$$r_{it} = E(r_i) + ((1-\alpha_{it})\beta_i e_{mt} + \delta_{it}) = E(r_i) + e_{it}. \tag{1.9}$$

Since we need to have $e_{mt} = \sum_i w_{it} e_{it}$, together with above equation this condition implies that $e_{mt} = \frac{\sum_i w_{it}\delta_{it}}{1-\sum_i w_{it}(1-\alpha_{it})\beta_i}$. Since the original CAPM holds in terms of $E(r_i)$ and $E(r_m)$, we can derive the relationship for the observed market returns by substituting equations (1) and (3) into (8):

$$r_{it} = \beta_i r_{mt} + \alpha_{it}\zeta_{it} + \delta_{it}, \tag{1.10}$$

where $\zeta_{it} = \frac{-\beta_i \sum_i w_{it}\delta_{it}}{(1-\sum_i w_{it}(1-\alpha_{it})\beta_i)}$. Therefore, Market Model error consists of two parts:

$$\eta_{it} = \alpha_{it}\zeta_{it} + \delta_{it}. \tag{1.11}$$

[9] The term is related to the model uncertainty discussed, for example, in Cao, Wang, and Zhang (2005).

[10] Here we assume that investors arrive at average return via trade.

We do not attempt here to analyze the second part, instead, we'll concentrate our attention on the first, since we are able to make certain statements about behavior of alpha. This part of the error is smaller if the investors use the Market Model in security evaluation decisions. Its magnitude depends on how noisy is the idiosyncratic source of information. From equation (1.6) α_{it} converges to one as $\sigma^2_{\nu i}$ converges to zero (idiosyncratic source is fully informative) and to zero as $\sigma^2_{\nu i}$ converges to infinity (idiosyncratic source is very noisy). In the former case, $\alpha_{it} = 1$ and the model's error takes the form: $\eta_{it} = \zeta_{it} + \delta_{it}$. Investors use only their (precise) estimates of security returns as there is no need to rely on aggregate market data. If, on the other hand, little information is present to evaluate stock i, investors rely exclusively on the Market Model. In this case $\alpha_{it} = 0$ and the Market Model error is just δ_{it}, i.e., the deviations from the CAPM equilibrium are smaller because market participants set their expectations according to the Market Model. The resulting returns behave as the investors expected, and according to the Market Model equation. The idiosyncratic risk in this case will also appear to be smaller in magnitude.

The variance of the (first part of) error in this modified Market Model is thus a function of the ratio $\frac{\sigma^2_{\nu it}}{\sigma^2_{mt}+\sigma^2_{\nu mt}}$, which is not quite empirically tractable. We therefore need an additional proposition.

Assume that σ^2_{mt} and $\sigma^2_{\nu it}$ are roughly constant over a short period of time. The remaining variable in the above ratio ($\sigma^2_{\nu mt}$) is the variance of the error of the adopted measure of market index. Its large values indicate that the true index is not measured well. We hypothesize that when market value is concentrated in a fewer number of securities conventional measures such as DJIA or S&P500 are better proxies of the market index. Additionally, even if the market index is exactly measured, it is easier to access its value if market is highly concentrated. Therefore, the magnitude of $\sigma^2_{\nu mt}$ is smaller. In this case investors place greater emphasis $(1 - \alpha)$ on the Market Model source of information, thereby decreasing variance of the model error. A natural measure of this effect is the concentration of market value, which is computed similar to the Herfendahl index, and is therefore referred to here as the "Quasi-Herfendahl Index":[11]

$$\gamma_t = \sum_i w_{it}^2. \tag{1.12}$$

where w_{it} is the market value weight of security i.

Based on the above discussion we can determine the relative gain of using firm-specific versus market index information:

$$\frac{\sigma_{\nu i}^2}{\sigma_m^2 + \sigma_{\nu mt}^2} = f(\gamma_t), \tag{1.13}$$

where $f(.)$ is some function of γ_t. For tractability we assume a linear relationship of the form:

$$\frac{\sigma_{\nu i}^2}{\sigma_m^2 + \sigma_{\nu mt}^2} = \vartheta\gamma_t, \tag{1.14}$$

where ϑ is positive. Therefore, the Market Model becomes:

$$r_{it} = \beta_i r_{mt} + \frac{\beta_i^2}{\vartheta\gamma_t + \beta_i^2}\zeta_{it} + \delta_{it}. \tag{1.15}$$

From equation (1.15) we can see that Market Model error fluctuations are smaller when market value is more concentrated, because it is easy to evaluate stock returns using the index. This task is simplified further when a stock is not very sensitive to the market's movements (i.e., its beta is relatively small). The opposite is also true: when the market has dispersed weights and the beta of a given security is large, it does not pay off to rely on the Market Model in evaluation of individual securities.

Some additional intuition can be gained if we consider the analogy to the theory of gravitational attraction: objects with non-zero masses attract each other. The attraction force is stronger the greater the mass of the objects. Imagine a region of space filled with interstellar dust. If the dust particles are evenly spread the attraction among them is weak. If the particles are arranged into clusters (with large masses)

[11]In the economic literature, the Herfendahl Index measures the degree of competition and is computed as the sum of the squared market shares of the firms in an industry or market.

they are more likely to attract each other and the surrounding dust. Suppose now that mass is the market capitalization weight and particles are traded securities. When investors form their expectations about stocks by looking at the behavior of a set of large stocks, they create a "gravitational field" among securities (over and beyond their fundamental co-movements) similar to the one observed in nature. This field is stronger in a more concentrated market. The variable γ_t is a measure of the strength of this field.

Suppose the market (which consists of thousands of stocks) has a well-defined cluster of large companies. It is easier in this case to anticipate the movements of the market index as you only need to know the behavior of the few main companies. Investors know that all returns follow the Market Model. Further, the model has better predictive power, and is more useful to investors, while collecting information about individual companies is still costly. Investors therefore rationally decide to form their evaluations of returns based more on the Market Model than on individual security information. But in equilibrium the returns of the stocks adjust according to investors' expectations. This creates additional correlations among stock returns in the market.

Equation (1.15) suggests that idiosyncratic volatility depends upon a macroeconomic variable that measures the degree of market participants' reliance on a market index in the evaluation of future returns. To the extent that this variable records low variability in a short period of time (e.g., one month), the measured idiosyncratic volatility should be its function. In fact, it is *conditional* idiosyncratic risk that is being picked up in the monthly idiosyncratic risk measure, where γ_t is the relevant information set. Taking a linear approximation of the coefficient on η_{it} with parameters α_0 and α_1 (and assuming that β_i is constant), we have the following expression for the conditional idiosyncratic risk of security i:

$$IR_{it} = \alpha_{i0} + \alpha_{i1}\gamma_t. \tag{1.16}$$

where α_{i0} and α_{i1} are some constants. If idiosyncratic risk and γ_t are integrated variables, they should have a long-run equilibrium relationship. Averaging across stocks we obtain a similar expression for the average conditional idiosyncratic risk:

$$IR_t = \alpha_0 + \alpha_1 \gamma_t, \tag{1.17}$$

where the coefficients are the cross-stock coefficient averages. This analysis suggests that individual as well as average idiosyncratic variances should be cointegrated with γ_t and this relationship should not depend on the set of stocks included in the measure of the average idiosyncratic volatility.

1.4 Testing, data, and results

Under several reasonable assumptions we establish in the previous section that the concentration of market value is related to changes in the idiosyncratic risk of individual securities and to changes in the market's average idiosyncratic risk. These propositions are easily tested empirically. The tests that follow are divided into four groups according to the level of aggregation of the average risk: the market average idiosyncratic risk, industry average risk, selected average risk, and individual security idiosyncratic risk.

1.4.1 Analysis of market average idiosyncratic volatility

In the first group of tests we use five methods to estimate idiosyncratic volatility in an effort to ensure that the results are not affected by differences in the estimation procedures. With robustness established, we continue to use only the first method in the remaining three groups of tests. The estimation methods are:

1. CLMX procedure using the equally weighted market index (LIRCE),

2. CLMX procedure using the value weighted market index (LIRCV),

3. the Market Model (one-factor) residual volatility (LIR),

4. the Fama and French three-factor model residual volatility (LIRFF),

5. the Market Model residual volatility estimated using five-year interval regressions (LIR5Y).

The first method, described in detail in Campbell, Lettau, Malkiel, and Xu (2001), is appealing since it does not require estimation of betas. Assuming zero cross-correlation among betas the monthly idiosyncratic risk is constructed as follows:

$$IR_t = \frac{1}{j}\frac{1}{n}\sum_{i=1}^{j}\sum_{s=1}^{n}(r_{is} - r_{ms}), \tag{1.18}$$

where r_{is} is the return on security i on day s in month t, r_{ms} is the market return on day s in month t, j is the number of firms in a given month, and n is the number of days in a given month. All other volatility measures are monthly averages of the residuals, so the time series consists of monthly data for the July 1963 to December 2004 period. The original data set includes daily data for all the stocks traded on NYSE, NASDAQ, and AMEX during the specified period (obtained from the Center for Research in Security Prices (CRSP) database).

The measure of the concentration of market value is the same in all of the tests and is constructed using monthly data on market capitalization weights (w_{it}) of all the securities in the sample:

$$\gamma_t = \sum_{i=1}^{j}(w_{it}^2). \tag{1.19}$$

All variables in this study are converted into logarithms following the convention adopted in the literature.

The empirical analysis in this paper implies testing for the existence of a linear relationship between two time-series variables. If these variables are non-stationary, we need to rely on the concept of cointegration. The first step, therefore, is to establish stationarity properties of the variables of interest. An Augmented Dickey-Fuller procedure is used for this purpose. The next step is cointegration analysis, in the event both of the variables in the tested relationship are non-stationary. We apply the Johansen methodology (Johansen (1991) and Johansen (1995)). The specification we use allows the series to have linear trends. The likelihood ratio trace statistic is computed as follows:

$$Q_0 = -T \sum_{i=0}^{1} log(1 - \lambda_i), \tag{1.20}$$

where λ_i is the i-th largest eigenvalue. It is the test of H(0), no cointegrating equations, against H(1), one cointegrating equation. The critical values for the test are obtained from Osterwald-Lenum (1992). After cointegration is established, we estimate a vector error correction model (VECM) to infer the direction of causality among the variables. Our model predicts that idiosyncratic volatility is endogenous in this relationship. The VECM estimated for idiosyncratic risk and γ_t, respectively, is the following:

$$\Delta IR_t = \varphi_{01}+\varphi_{11}(IR_{t-1}-\phi\gamma_{t-1})+\varphi_{12}\Delta IR_{t-1}+\varphi_{13}\Delta IR_{t-2}+\varphi_{14}\Delta\gamma_{t-1}+\varphi_{15}\Delta\gamma_{t-2}, \tag{1.21}$$

and

$$\Delta\gamma_t = \varphi_{02}+\varphi_{21}(IR_{t-1}-\phi\gamma_{t-1})+\varphi_{22}\Delta IR_{t-1}+\varphi_{23}\Delta IR_{t-2}+\varphi_{24}\Delta\gamma_{t-1}+\varphi_{25}\Delta\gamma_{t-2}, \tag{1.22}$$

where IR_t is a measure of idiosyncratic risk, γ_t is the market concentration index, and $(IR_t - \phi\gamma_t)$ is the error correction term (ECT).[12]The significance of the coefficients on the ECT in each equation can tell us which variable in the system is exogenous. We expect that γ_t is exogenous and φ_{21} is insignificant.

[12]In untabulated tests (available upon request), specifications with a different number of lags yield similar results.

As we mention earlier, idiosyncratic volatility of economic fundamentals (earnings and cash flows) is shown to be related to average idiosyncratic variance (see, for instance, Irvine and Pontiff (2005)). We need to make sure that the variable of interest (γ_t) does not proxy for this measure. These robustness checks are included in the first group of tests. We reconstruct the three measures of the idiosyncratic volatility of fundamentals (sales, earnings, and cash flows) following Irvine and Pontiff (2005) and test whether they are related to the concentration of market value.

The three measures are obtained using the following algorithm (applied in Irvine and Pontiff (2005)). Sales per share, earnings per share, and cash flows per share are computed using COMPUSTAT data items 2, 5, 14, 15, and 19 (quarterly data). Specifically, earnings per share is item 19, cash flows per share is item 5 plus item 19, and sales per share is item 2 divided by item 15. All the variables are divided by the price (item 14) and ranked into 100 groups by this ratio. If an observation has the highest rank, it is being assigned the maximum value from the previous rank group. If an observation has the lowest rank, it is being assigned the minimum value from the previous rank group. This procedure is introduced by Irvine and Pontiff (2005) to correct for outliers. The variables are then multiplied back by the price. Next, shocks to the fundamentals are computed as the errors from the following regression:

$$E_{it} - E_{it-4} = \alpha + \beta_1(E_{it-1} - E_{it-5}) + \beta_2(E_{it-2} - E_{it-6}) + \beta_3(E_{it-3} - E_{it-7}) + e_{it}, \tag{1.23}$$

where E_{it} is the firm-level earnings, cash flows, or sales at quarter t. The (quarterly) residuals of this regression are then converted into daily data by assigning the same value to each day of a given quarter. The market index for each of the fundamental measures is the moving average of the index computed using the equally weighted average across the firms. The idiosyncratic fundamental volatility measures are monthly averages (across firms) of the deviation of these errors from the moving average index.

Empirical results

Our data set consists of the five measures of idiosyncratic risk, the Quasi-Herfindahl Index (γ_t), the three measures of idiosyncratic fundamental volatility constructed using sales, cash flows, and earnings (LIS, LICF, and LIE, respectively), and the total number of securities on the market (LNS). Table A.1 contains descriptive statistics for all these variables. The five idiosyncratic risk measures are virtually identical in their major statistical indicators and are highly correlated (Table A.2). Figure A.1 depicts the first measure of idiosyncratic volatility (LIRCV) as a function of time. The trend found in various studies for the years 1963 to 2000 is clearly visible. Note also the sharp decline in volatility after 2000, as pointed out in several recent papers (see, for example, Brandt, Brav, and Graham (2005)). The time series of the concentration measure is plotted in Figure A.2. Unlike idiosyncratic volatility, it is decreasing over time. All measures of idiosyncratic volatility are correlated with γ_t (correlation coefficient is about -0.7), supporting our hypothesized relationship.

Different idiosyncratic fundamental volatility measures vary in the major statistical indicators (Table A.1), though all are correlated with the average coefficient of 0.7. They are plotted (against the time line) in Figure A.3. All three have a slight positive trend, consistent with Irvine and Pontiff (2005). Idiosyncratic volatility of sales and cash flows are not highly correlated with γ_t (correlation coefficient is about -0.3), in contrast to the volatility of earnings (correlation with γ_t is -0.57), which may potentially account for the relationship between γ_t and idiosyncratic risk (in case it is cointegrated with γ_t). All measures of fundamental idiosyncratic volatility are correlated with idiosyncratic risk, with coefficients between -0.5 and -0.8, suggesting the existence of a relationship. The last variable (number of securities in the market) also trends upwards and is correlated with γ_t for each of the measures of idiosyncratic risk (see Figure A.4). Thus, it can potentially account for the changes in idiosyncratic risk. Note that we use the number of securities in the market in the robustness checks to ensure that γ_t does not proxy for this variable.

Augmented Dickey-Fuller unit root tests indicate that all of the considered variables are non-stationary, as we are unable to reject the unit root hypothesis (Table A.3). Results of Johansen cointegration tests for each of the measures of idiosyncratic risk and the market concentration are summarized in Table A.4. Likelihood ratio statistics indicate the existence of a cointegrating equation at the 5% level for each of the measures of idiosyncratic risk. The estimated coefficients in the cointegrating equation (Table A.5) confirm the direction of the relationship predicted by the theory (negative). The normalization variable is idiosyncratic risk, as the theory suggests it is the endogeneous variable in the system. Whether this is indeed the case will be studied next in the analysis of the error correction model.

Table A.6 contains estimates of the VECM for each of the five idiosyncratic volatilities. The results do not vary much across the volatility measures. The coefficients on the error correction term (ECT) in equation (1.21) are highly significant (t ratios are slightly over 4.0 for all five measures), while coefficients on this regressor in equation (1.22) are insignificant (t statistics are about -0.8). This indicates that γ_t is not affected by the deviations in the relationship between concentration and idiosyncratic risk, i.e., it is exogenous. Applying similar logic, we conclude that idiosyncratic risk is endogenous in this relationship, i.e., the concentration measure evolves independently, while idiosyncratic risk adjusts to concentration in equilibrium.

Note as well the significance of some of the lagged variables: lagged changes in idiosyncratic risk are significant in equation (1.21), while both the first and second lags of the past changes in γ_t are insignificant. The importance of the lagged variables may be an indication that the relationship between γ_t and idiosyncratic risk accounts only for a part of the overall dynamics of the latter. Other factors may also explain the changes in idiosyncratic risk, as documented in recent research (such as breaking up conglomerates, increased institutional ownership, volatility of betas, etc.; see Section

2). The significance of the lags of idiosyncratic risk is consistent with the GARCH framework and with the significance of the "GARCH" parameters in the variance equation (see Section 4.4).

Next, we want to make sure that the variable γ_t, which appears to drive the changes in idiosyncratic risk, is not just a proxy for changes in fundamentals or in the number of securities. We use the three measures of fundamental volatilities suggested in Irvine and Pontiff (2005), namely, the average idiosyncratic volatility of earnings, sales, and cash flows, to test whether each is cointegrated with γ_t (Table A.7). In most cases the idiosyncratic fundamental volatility and the total number of firms are cointegrated (at least at the 5% level) with the measures of idiosyncratic risk, as expected. The measure of the fundamental volatility using earnings is cointegrated only with the LIR and not with the other measures of average idiosyncratic risk. None of the fundamental volatilities nor the number of securities is cointegrated with γ_t, suggesting that these variables cannot account for the cointegration between the latter and the average idiosyncratic risk.

1.4.2 Analysis of industry average idiosyncratic volatility

The theoretical derivations suggest that it should not matter for the results which securities are included in the average idiosyncratic risk. The conclusions should hold, therefore, for an individual industry (i.e., when the average firm-specific variance measure is computed within each industry). We proceed with the second set of tests by grouping the securities into industries according to the industry classification in Fama and French (1997).[13] We also construct γ_t within each industry to compare its influence on the industry average idiosyncratic risk to that of the total market concentration. Although the theory predicts that idiosyncratic risk is related to the

[13] They define 48 industries; the SIC codes not accounted by this classification are combined into industry 49.

total market concentration measure, looking at the industry-specific concentration may be an interesting exercise as it can reveal the potential importance of stock market industry segmentation since there is no industry factor included in the Market Model. To the extent that the within-industry γ_t determines the dynamics of its average idiosyncratic risk, each industry can itself be treated as a market. This can arise, for example, if certain barriers to cross-industry investment exist or when within-industry information dominates the influence of the outside world.

Empirical results

The results are summarized in Table A.8. Columns 3 and 5 contain the statistics of the ADF unit root test for each variable. The last two columns report cointegration tests for industry average idiosyncratic risk and both the within-industry and the market total γ_t's. We can only test for cointegration between the variables that are I(1). There are 35 such pairs among the 49 industries. Thirty of these 35 pairs record a significant cointegrating relationship at the 5% level (at least) with industry γ_t or the market γ_t: 14 (15) industries are cointegrated with the market γ_t at 1% (5%) level, and for industry γ_t the corresponding number is 6 (15). Only five industries do not exhibit any relationship with either the within-industry or the market-wide value concentration: pharmaceuticals, precious metals, utilities, banking, and real estate. For the remaining 30 we proceed with the estimation of the cointegrating equation and the VECM.

Table A.9 contains the estimated coefficients on the concentration of market value in the cointegrating equation (coefficient on idiosyncratic risk is normalized to -1), and the t statistics for the error correction term in the equations of dynamics for both of the variables. As before, we expect to find an inverse relationship, i.e., that the cointegrating equation coefficient on γ_t (γ_t^i) is negative. Additionally, we expect that the t statistic is significant in the equation for the changes in idiosyncratic risk and insignificant in the equation for the changes in γ_t. The results confirm these expectations whenever the total market measure of value concentration is used. All of the γ_t coefficients are negative (ranging from -1.042 to -0.441) and the t statistics on the error correction term in the equation for changes in idiosyncratic risk are significant (at least) at 1% level, indicating that idiosyncratic risk is the endogeneous variable in the relationship. All except one of the t statistics for the equation of the concentration dynamics are insignificant at the 1% level (the Fabricated Products industry has a t statistic of 2.12, which is significant at the 5% level), suggesting that γ_t is exogeneous.

However, the results are not quite as expected when the within-industry measure of market concentration is used in the analysis. Ten out of 21 industries record a positive sign on the γ_t in the cointegrating equation. All of the t statistics in the idiosyncratic risk dynamics equation are significant, but seven of the industries also have a significant t in the equation for the γ_t dynamics. This points to the possibility that both concentration and idiosyncratic risk are endogenous, i.e., the causality runs in either direction. This evidence can partly explain the "wrong" sign in the cointegrating equation: in five cases a positive sign in the equation coincides with the significance of the t statistics. One reason could be that the influence of γ_t on idiosyncratic risk outweighs that of idiosyncratic risk on γ_t, thereby changing the sign of the relationship.

The results indicate that both within-industry γ_t and market-wide γ_t have an effect on the industry average idiosyncratic volatility, the second being somewhat stronger. As the evidence suggests, in certain industries local value concentration appears to affect industry average idiosyncratic risk. This can be the case if, for example, investors rely primarily on within-industry (along with the market-wide) factors in security evaluation. Additionally, the data suggest that there are cases in which a relationship exists between γ_t and the idiosyncratic risk of different industries (results are not reported), which could mean that factors in one industry affect security evaluation in another.

1.4.3 Analysis of the selected average idiosyncratic risk

So far we have established that average idiosyncratic risk and a measure of the concentration of total market value are related in the predicted manner. This result is not driven by changes in the fundamental idiosyncratic volatility or in the number of securities in the market. There is the possibility, however, that the resulting relationship between the concentration of market value and average idiosyncratic risk is driven by changes in market security composition (even if the average idiosyncratic risk is measured as a simple average). For instance, adding small stocks with high idiosyncratic volatility may affect both the average idiosyncratic risk and γ_t. To address this concern we use the third group of tests, in which an average idiosyncratic risk measure is constructed using only those securities that existed in the market for the entire time span considered in the paper.[14]By construction, this index cannot be affected by changes in market composition. To address this issue further, in the next section we check whether the connection exists at an individual security level for the 30 companies from the Dow Jones Industrial Index.

The cointegration analysis cannot be applied directly to the average idiosyncratic risk of the securities that existed for the whole sample period. The problem is this variable appears to be stationary (while γ_t is non-stationary, as before). This fact does not imply that these two variables cannot be related. Suppose idiosyncratic risk consists of two parts, both of which are non-stationary, while their sum is stationary. If one of these parts is cointegrated with γ_t, idiosyncratic risk and the market value concentration are related, but the deviations from their (linear) combination may

[14]This test relies on the assumption that these returns are independent from the returns of the other companies in the market.

not necessarily be stationary. We apply the VECM framework to test whether the dynamics of idiosyncratic volatility is affected by the errors in the idiosyncratic risk - concentration relationship (ECT). The testable hypothesis is the significance of the ECT in the regression for the dynamics of selected average idiosyncratic risk.

Empirical results

The results are summarized in Table A.10. The ECT is obtained from the regression of the selected average idiosyncratic risk on γ_t. This term is significant at the 1% level in the regression of changes in idiosyncratic risk, while it is insignificant in the regression of changes in γ_t, indicating that there is a relationship between the two variables and that it is γ_t that is causing changes in idiosyncratic volatility in the long run, as expected. A concern still exists that the distribution of the estimated standard errors for the coefficient on the error correction term may be non-Normal (since the deviations from the concentration-idiosyncratic risk relationship are possibly non-stationary). To address this issue we add non-parametric bootstrap estimated standard errors, which appear on the line below the regularly estimated errors in Table A.10. The bootstrap standard errors do not change any of the significance levels on the error correction terms and therefore confirm previous results.

1.4.4 Analysis of the idiosyncratic volatility of individual securities

The arguments in the previous section suggest that the concentration of market value should affect the variance of Market Model error for an individual security as well. In the last group of tests we verify this hypothesis using the GARCH framework (see Bollerslev (1986)), which allows us to directly model the effect of concentration on the Market Model variance. We assume that Market Model error follows a GARCH process:

$$r_{it} = \omega_0 + \psi_0 r_{mt} + \psi_{01} r_{smbt} + \psi_{02} r_{hmlt} + \epsilon_{it}, \tag{1.24}$$

and

$$h_{it} = \omega_1 + \psi_1 h_{it-1} + \psi_2 \epsilon_{it-1}^2 + \psi_3 \gamma_t + e_{it}, \tag{1.25}$$

where r_{smbt} and r_{hmlt} are the two Fama-French factors, ϵ_{it} is distributed as $(0, h_{it})$, and h_{it} is the conditional variance of the error term. We are interested in the significance and the sign on the coefficient ψ_3, which indicates whether γ_t affects the variance in the hypothesized direction. We estimate the model by Quasi-Maximum Likelihood. Analysis of individual securities is performed on the sample of 30 stocks that comprise the Dow Jones Industrial Index as of December 2005.

Empirical results

The idiosyncratic risk of the Dow Jones Industrial securities appears to be stationary (results are not reported). We therefore omit the cointegration analysis and instead use the GARCH model to test whether market concentration affects the variance of each individual security as predicted. It is expected that concentration should enter the variance equation with a negative and significant sign. Table A.11 contains the results for all 30 companies. In 19 out of 30 cases, γ_t appears significant (at the 5% level at least) in the variance equation and has the expected negative sign. In five cases the variable is significant but the sign is reversed. The inclusion of the concentration measure does not render either of the ψ_1 or ψ_2 coefficients insignificant, indicating that γ_t does not proxy for the ARCH effects. The analysis therefore suggests that the market concentration affects Market Model error variance directly and not as a result of the averaging of idiosyncratic risk.

1.5 Conclusions

The results in this study show that in general Market Model residual variance is inversely related to the concentration of total market value, which measures the ability of investors to rely on the market index to evaluate individual securities. The relationship between these two variables emerges both when the Market Model is used by market participants to price individual securities and when a higher market value concentration increases its usefulness. In particular, we find that a decrease in a measure of the concentration of market value (γ_t) can at least in part explain the recently discovered trend in the average idiosyncratic volatility in the U.S. market. This variable is also often able to account for changes in firm-specific risk averaged by industry. An index of within-industry concentration of market value is also shown to be related to industry average idiosyncratic volatility, although not always in the way that is expected. Finally, the idiosyncratic risk of individual securities in the sample of the 30 Dow Jones Industrial Index companies also exhibits the predicted relation with respect to the concentration of market value.

Analysis of the error correction model indicates that causality runs in the direction of idiosyncratic volatility, confirming our model predictions. Various measures of fundamental idiosyncratic volatility and the total number of securities in the market do not account for the observed relationship.

This paper considers general consequences of investors relying on the Market Model to evaluate individual securities. To ensure empirical tractability we use the market value concentration index as a measure of the usefulness of this source of information. Other measures may be considered in future research. For example, one could use models in which forecasts of the market index are based on the values of certain macroeconomic variables (e.g., interest rates or GDP) or on the past values of the index itself. Additionally, the market value concentration and its influence on stock return correlations can be measured using something other than the suggested index. Measures can be constructed that account for such factors as the distance between the companies or whether they operate in the same industry. Finally, one could consider further intra-industry information spillovers and their effect on the present analysis.

CHAPTER 2

Cross-Section of Trends in Firm-Specific Risk

2.1 Introduction

There has been a considerable debate in the literature during the last few years related to findings in Campbell, Lettau, Malkiel, and Xu (2001) (henceforth CLMX). CLMX demonstrates the evidence that average idiosyncratic risk in the US economy has been steadily increasing for over four decades. The authors suggest their findings have important portfolio implications, i.e. investors nowadays need to hold a larger number of securities in their portfolios to achieve reasonable diversification effects. More recent research though indicates that the trend has reversed in the last several years (see Brandt, Brav, and Graham (2005)). This issue has quickly gained popularity in the finance literature and 'currently is one of the most actively researched asset pricing puzzles' according to Brandt, Brav, and Graham (2005).

Mechanically, the trends of market average idiosyncratic volatility can only be caused by a combination of the following sources: new listings, delistings, and existing firms with positive, negative, or no trends. These difference sources, however, have drastically different investment implications. If only new issues contribute to an increasing average idiosyncratic risk, investors do not need to adjust their portfolios of existing securities in order to keep the level of portfolio risk constant. On the other hand, if most firms experience a positive trend in idiosyncratic risk, then, as CLMX argue, the number of securities included in the portfolio needs to be increased to achieve the same level of diversification. Further, if some firms experience positive volatility trends but some other experience negative trends, then the implication on diversification will be quite different depending on the stocks included in the portfolio. Therefore, it is crucial to determine exactly which of the specified sources contributes to the dynamics of average idiosyncratic risk.

We estimate the firm-by-firm trends in securities' idiosyncratic risk. By doing so we can identify precisely the contribution of the above sources to the market average idiosyncratic volatility. We have two major findings in this regard. First, we confirm the finding by some studies (e.g., Brown and Kapadia (2006), Fink, Fink, Grullon, and Weston (2005), Wei and Zhang (2006)), Bennett and Sias (2005)) that new listings are an important factor driving the variation of market average volatility. However, different from this studies, we show that new listings are far from being the only driver. For example, we show that a subsample of firms existing since 1980 exhibit very similar trends of average volatility as those of the whole market. That is, the average volatility trends are also observed in existing firms.

Second, while existing securities on average show the same patterns as the full sample (including new listings), it does not mean that most existing firms follow the same trends. Rather, there is a rich cross-section of the trends of idiosyncratic risk. We find that, during the period with an increase of average voltility, about 30% of fimrs have a significantly positive trend, while about 20% have a significantly negative trend. These two groups can cancel each other in the market average. This in part explains why previous studies which concentrated on the analysis of the various market averages of idiosyncratic risk rather then individual companies, concluded that the trends in idiosyncratic risk of the existing securities are negligible. We demonstrate further that the two groups' relative contribution to the market average idiosyncratic risk changes from period to period. In 1986 - 1990 the influence of the trends in existing firms came largely from the group with a positive trend in firm specific risk, while after 2002 the negative trend group played the dominant role.

We further depart from the current literature by exploring the factors that cause the cross-sectional difference in volatility trends. We achieve this task by comparing firm-by-firm volatility trends to firm-by-firm trends in firm characteristics such as earnings, earnings volatility, institutional ownership, price level, and trading volume. This exercise allows us to test three main interpretations in the current literature.

1. **Fundamentals.** Wei and Zhang (2006) and Irvine and Pontiff (2005) suggested that the trend can be attributed to the behavior of fundamentals (i.e. earnings, sales or cash flows). Our evidence confirms that fundamentals play a significant role in the explanation of trends. In particular, we find that firms with increasing earnings and decreasing earnings volatility are more likely to have a decreasing risk.

2. **Institutional ownership.** Malkiel and Xu (2003) linked the increase in idiosyncratic risk to the growing share of institutional ownership. We first confirm their results using our sample, and then show that this link exists because institutional ownership serves as a proxy for other firm characteristics. When more firm characteristics are considered, a significantly negative relation between firm-specific volatility trend and firm-specific institutional ownership is observed. That is, relative to other firms, those with increasingly more institutional ownership are more likely to experience a decrease in volatility.

3. **Speculative trading.** Brandt, Brav, and Graham (2005) argued that bursts in idiosyncratic volatility were temporary phenomena associated with increased speculative trading concentrated in low-priced stocks. We find that trends in

stock price do account for the cross-sectional variation of trends in risk. Similar to results in Brandt, Brav, and Graham (2005) we observe that a firm with increasing risk is likely to have a decreasing price of equity. On the other hand we find that a positive trend in security turnover implies a negative trend in idiosyncratic risk. Therefore, at least for most stocks, increased trading does not lead to increase in stock volatility.

Our findings contribute to an increasingly large literature that studies average volatility trends, including among others, Rajgopal and Venkatachalam (2007), Arena, Haggard, and Yan (2005), Cao, Simin, and Zhao (2006), Guo and Savickas (2007), and Kelly (2005). Most of these papers have studied variously composed averages of idiosyncratic risk. None so far, to the best of our knowledge, has used a firm-by-firm estimation of idiosyncratic risk. This approach does allow to distinguish among the three sources of changes in the market average which we have mentioned earlier. Our contribution therefore lies in precise identification of the sources of the trend in average idiosyncratic risk.

Our paper also has direct implications on studies that investigate whether idiosyncratic risk is priced (such as Ang, Hodrick, Xing, and Zhang (2006), Spiegel and Wang (2006)). The cross-sectional difference of volatility trends suggests interesting time series dynamics of cross-sectional expected returns related to volatility. We explore these issues in future studies.

The paper is structured as follows. Section 2 provides the analysis of the trends in idiosyncratic risk at the security level and the contribution of each type of security to the average idiosyncratic risk in the economy. In section 3 we relate the trends in the firm characteristics to the trends in firm specific risk and investigate the relative role of the three proposed hypothesis. Section 4 concludes with a discussion.

2.2 Cross sectional variation of trends in idiosyncratic risk

In this section we will precisely determine the mechanical sources of the trend in the average idiosyncratic risk. These sources are important to know given their dramatic portfolio implications. Only firm-by-firm estimation would allow us to identify contribution of each firm to the total changes in idiosyncratic risk. We first divide the market into groups of securities with different trends (positive, negative, and insignificant) and then examine contribution of each group to the changes in the overall market average idiosyncratic risk.

2.2.1 Data construction

Our data consists of the universe of daily returns of all the traded securities on NYSE, AMEX and NASDAQ markets for the period of July 1963 till December 2005. This time span is larger then the one originally considered in CLMX and allows us to track any differences between this period and the later years.

The idiosyncratic risk is estimated for each security as the monthly average variance of the residual from the Fama and French three factor model estimated month-by-month:

$$(r_{it} - r_{ft}) = \alpha_i + \beta_i(r_{mt} - r_{ft}) + \beta_{1i} smb_t + \beta_{2i} hml_t + e_{it}, \tag{2.1}$$

$$IR_{it} = \frac{1}{t}\sum_{s=1}^{t} e_{is}, \tag{2.2}$$

where r_{it} is return of stock i in period t, r_{mt} is the market return, r_{ft} is the risk-free rate, smb_t and hml_t are the Fama and French factor portfolios. We require for statistical accuracy at least ten daily return observations for each firm in a given month for the monthly estimate of idiosyncratic risk to be included in the analysis.

We then estimate the trend for the life span of each security and require that at least two years of monthly idiosyncratic risk data to be available for each stock. As Table B.1 indicates there are 21860 firms which meet these requirements for the period July 1963- December 2005. We run least squares regressions of idiosyncratic risk on the time trend to obtain the estimates of the trend coefficients and their t statistics for each security:

$$IR_{it} = \alpha_0^i + \alpha_1^i t + v_{it} \tag{2.3}$$

CLMX suggested that due to large autocorrelation in idiosyncratic risk the least squares estimates from such regressions may not provide a good measure of the trend coefficient. As a robustness check we re-run our results with the procedure they suggested for estimation of trend and find no significant difference from our original results (the sample size in this case is further reduced since the test requires inclusion of lagged values of idiosyncratic risk, as the result fewer firms have enough monthly data to obtain reasonable estimates).

2.2.2 Analysis of results

Proportions of positive, negative, and no-trend securities

Table B.1 reports relative proportions of positive, negative, and zero-trend securities in various time periods on US market. The first row of Table B.1 indicates that about 31% of the **total sample** of stocks exhibit positive significant trend (at least at 5% level) in firm-specific risk, while about 25% have negative significant trend. This leaves 44% of the market with no significant trend at the firm level. These proportions may **vary over time**. Brandt, Brav, and Graham (2005) for instance suggest that market average idiosyncratic risk shows periods of 'bubbles'. We therefore investigate the possibility of changes in these proportions over time.

CLMX and post-CLMX periods

We first split our sample into CLMX and post-CLMX periods. The trends are estimated separately for each of the two sub-samples. During CLMX period the proportions of the firms in each of the category are close to the ones observed in the total sample: 31% of stocks have positive trend, 21% have negaive trend, the rest have no significant trend.

The post-CLMX sample (1997-2005), which is characterized by decreasing idiosyncratic risk (see Brandt, Brav, and Graham (2005)), is different. Only 12% of the stocks have positive trend, while 46% have negative trend. Thus the proportion of the firms with no trends is roupgly the same as in the previous sample, but the proportions of the positive and negative trends in securities changed in favor of the latter. This in part explains the decline in the average idiosyncratic risk on the market in the last several years.

Ten years intervals

We further split our sample into **four time intervals** of about ten years each. The last four rows of Table B.1 contain the estimation results. The proportion of firms in each category varies from period to period. Positively trending securities had the largest share in the period 1963-1975 (39%), their share was the smallest during the last ten years (only 20%). Conversely, proportion of securities with negative trends was the largest in the last period (33%) and the smallest in the first period (about 6%).

Overall Table B.1 indicates that changes in proportions of the firms with positive and negative trends could be responsible for the changes in the average idiosyncratic risk in the economy. But the contribution of each group to the average risk depends on the relative magnitudes of the trend coefficients in addition to the influence of the proportions of each category. Therefore in the remainder of this section we quantify more rigorously the effects of each category on the market average idiosyncratic risk.

Relative contribution of positive versus negative trends

A. New lists versus existing securities in the total average idiosyncratic risk

First let us separate contribution of the trends in existing firms from that of the new lists to the trend in the total average. For this purpose we use the following procedure: all securities in the sample, which appear to have significant positive or negative trend, are assigned (to all the subsequent periods of their life) the value of idiosyncratic risk that they had at the time they were first listed. We therefore assume the idiosyncratic risk was constant (at the initial level) for each of these securities. The procedure removes the trends in idiosyncratic risk in existing firms along with the variation in the idiosyncratic risk around the trend line.[1] We then compute the average (across firms) of such constructed measure of idiosyncratic risk and compare it to the total average. The resulted series are depicted in Figure B.1.

The solid line is the average idiosyncratic risk with trends in idiosyncratic risk at the firm level removed (let us call it 'listing average'), so the only contribution to the changes in the average risk comes from the new listing or delisting of securities. As expected, this variable does not trend upward as much as the total average idiosyncratic risk. Comparing the slopes of the two trend lines we can conclude that about 70 % of the trend in the total average is due to the new firms, the remaining is due to the trends in the existing securities (Wei and Zhang (2006) provide similar conclusions using a different estimation method).

Also observe that before 1988 the two averages move very closely together, while after this date they diverge. For period 1988-1998 the listing average is below the total average, while after 2002 the inequality is reversed. These results suggest that for the first period the total average risk was increasing due to both addition of the

[1]If the variation of risk around the trend line is preserved, i.e. trend coefficient multiplied by the trend is subtracted from idiosyncratic risk, some of the risk observations become negative, which has no meaning in the present context.

new high idiosyncratic risk securities to the market and because a high proportion (or large trend coefficient magnitudes) of existing securities had a positive trend in their idiosyncratic risk. After 2002 the total average risk has decreased partly due to the addition of low idiosyncratic risk securities, and partly because the proportion of the existing securities with negative trends in their risk has increased (or magnitudes of the tend coefficients have decreased).

B. Positive versus negative trends in existing securities

The next two graphs (Figures B.2 and B.3) decompose further the effect of trends in existing securities into positive and negative trends. Figure B.2 compares the total average risk and the one where only positive trends at the firm level have been removed. For period 1988-1998 this new average mimics the listing average from the previous picture. This observation suggests that the effect of the trends in existing securities on the total average for this period came for the most part from the securities with positive trends. Figure B.3 plots the total average risk and the one where only negative trends have been removed. Comparing Figures B.1 and B.3 we conclude (using similar logic) that the effect of the existing trends on the total average was caused mostly by the negatively trending stocks after year 2002.

Together graphs B.1, B.2 and B.3 show that in different periods one of the effects (of positive or negative trends) in existing securities dominated in influence on the total average. Therefore the changing proportions of negative and positive trends in existing securities caused fluctuations around the trend line in the market average idiosyncratic risk.

C. Robustness checks

- Several studies (CLMX including) indicate that the observed trend is the most pronounced in the sample of the **NASDAQ** securities. We conduct a robustness analysis of our previous results by repeating Figure B.1 for the sub-samples of the NASDAQ and non-NASDAQ securities (Figures B.4 and B.5). The conclusions are effectively unchanged although the trend lines are more pronounced in the NASDAQ sub-sample, as expected.

- Taking out the trends in existing securities and comparing the resulting average to the total average idiosyncratic risk is just one way to quantify contribution of the trends in existing securities. Let us now consider an alternative approach. Figure B.6 shows the average risk constructed on **only the new firms** in each month. It is gradually increasing, indicating that the new lists contribute to the observed trend in the average. Figure B.7 shows the average idiosyncratic risk when the new firms are excluded in each month. This graph exhibits similar trend patterns as the simple average idiosyncratic risk, suggesting that the trend in the total average risk cannot be fully explained by the new lists.

- Finally, we take a sample of the firms that were first listed in January 1980 and trace their average idiosyncratic risk over time (Figure B.8). The graph clearly shows the same patterns as observed before: increasing risk until last several years, falling afterwords to its original level. This pattern therefore cannot be solely due to the addition of the new companies to the market over time.

D. Discussion

Our analysis in this section suggests that the contribution of the new lists, though considerable, cannot fully explain the observed behavior of the average idiosyncratic risk. The existing securities do exhibit significant trends in risk at the firm level. These trends affect non-trivially the total market average. About half of the firms in our sample have significant trends in idiosyncratic risk, 30 % with positive and 20 % with negative trend coefficients. These proportions change from period to period, causing changes in the relative contribution of each group to the total average. During period 1988-1998 the total average idiosyncratic risk is considerably higher due to the increased proportion of the firms with positive trends. Conversely after 2002 the total average risk is much lower due to a larger proportion of negatively trending securities on the market.

This evidence suggests that there may be some economy wide factors behind observed fluctuations in average idiosyncratic risk. This proposition is also supported by the results in CLMX that average idiosyncratic risk is related to the business cycle. Possibly, the market is less restrictive during some periods about the permissible quality of the stocks. This allows firms with high idiosyncratic risk to enter the market as well as existing companies to have higher risk of equity. Our evidence suggests that this process (if exists) is not monotonic in time. After the market downturn in 2001 we observe that majority of the new lists start having lower idiosyncratic risk, while existing securities are more likely to have a decreasing risk. In other words, it appears that the market have become more restrictive about the risk of its securities.

2.3 Factors that explain cross-section of trends in idiosyncratic risk

2.3.1 Explaining probabilities of a trend

We found out in the previous section that idiosyncratic risk in cross-section of securities may have positive, negative trend or no trend at all. The trend in the average idiosyncratic risk on US financial market is the result of the effects of the newly listed or delisted securities in every period, as well as the trends at the levels of the existing securities. The latter contribution is non-negligible, even though the influence of the trends at existing securities is not easily observable in the average due to partial cancellation of positive and negative trends. The existence of statistically significant trends at the firm level has implications not only for the behavior of the average idiosyncratic risk in the economy but also for portfolio strategies, which we discussed earlier in the paper. Therefore it is of research and practical interest to know what other characteristics distinguish the firms with positive, negative, or zero trend and what are the economic factors which explain this cross-section.

In this section we ask the following question: given the observable data on firm characteristics, which of them can explain the presence of trends in the firms' idiosyncratic risk? Since constantly increasing (or decreasing) risk is likely due to constantly increasing (or decreasing) firm characteristics, we compare (in the analysis that follows) appearance of trends in idiosyncratic risk of each security to the appearance of trends in its characteristics in the cross section of traded securities.

Data construction and methodology

The data is obtained from COMPUSTAT (quarterly frequency firm characteristics), CRSP (monthly frequency returns) databases and 13(F) filings (quarterly frequency institutional ownership). We include in the analysis the following characteristics, which are most commonly used in the literature related to this topic: firm size (measured as the log of the market value of the firm adjusted by the level of inflation (CPI), the market value of equity is computed as the closing end of period price of security multiplied by the number of shares outstanding); book-to-market value (the book value of equity is computed (following Fama and French (1992)) as the COMPUSTAT data item 60 (if available, otherwise data 59+55 or 44-54, in this order) plus data 52 minus data 55); cash ratio (cash ratio is data 36 over the total assets (data 44)); earnings per share and its volatility (the volatility of firms' earning per share is computed using the five year rolling estimates of the variance); leverage (the leverage ratio is equal to the book value of long-term debt (data 51) divided by the total book value of assets (data 44)); turnover; R&D expenditure; institutional ownership share; return and price (adjusted for inflation).

Table B.2 contains the main statistical indicators of the major firm characteristics. Trends in firm characteristics at the security level are estimated using the same approach as we used in estimation of trends in idiosyncratic risk.

Analysis of the results

A. Univariate analysis for each characteristic

First we would like to compare the appearance of trends in firm characteristics versus trends in risk separately for each characteristic. Results are summarized in Table B.3. Each entry of the table represents the number of securities in the sample that have statistically significant trends both in the corresponding characteristic and in the risk. The sample shares (in %) are given in parenthesis and sum to 100% (total sample) for each characteristic. The last line of the table summarizes unconditional appearance of each type of trend in the firm characteristic (similar to entries in Table B.2 for idiosyncratic risk). The line before last presents the correlation coefficients between the dummy for trends (positive, negative, and insignificant) in the firm characteristic and the dummy for trends in risk.

Observe from Table B.3 that a significant portion (60-70 %) of firms have statistically significant (at least at 5 % level) trends in firm characteristics. These trends therefore have a potential to explain the appearance of trends in idiosyncratic risk. Positive trends are more common then negative ones with a couple of exceptions (cash ratio and volatility of earning per share).

Let us now consider how often trends in each characteristic coincide with the trends in the security's idiosyncratic risk. For example, firms in our sample have positive trends in earning per share in 44% of the cases, but only in 10% of the sample securities have positive trends in **both** earnings and the risk. For negative trends this share is even smaller (2%). The trend in earning therefore is not very likely to explain the trends in idiosyncratic risk. This conjecture is confirmed further by an almost zero correlation coefficient of the dummies for the appearance of these two trends.

Of all the firm characteristics that we consider the largest (in magnitude) correlation coefficient belongs to the institutional ownership share (-0.127). Therefore trend in this variable is a good candidate for an explanatory factor of the idiosyncratic risk trends. The remaining variables have on average correlation coefficient of magnitude 0.05. Trend dummies for institutional ownership, price, return, and size are negatively correlated with the dummy for the trends in risk, meaning that positive trend in these characteristics is likely to imply a negative trend in idiosyncratic risk. On average positive (or negative) trend in a firm characteristic coincides with positive (or negative) trend in risk in 20-30 % of the cases.

According to the univariate analysis the least explanatory power with respect to trends in idiosyncratic risk can be attributed to earnings, turnover, earnings' volatility and R&D expenditure. The R&D variable may appear insignificant in part due to a poor availability of data. The final conclusions though about the role of each characteristic in appearance of trends in idiosyncratic risk cannot be made before we conduct a multivariate analysis since influence of one characteristic can obscure or enhance influence of another in the unconditional distributions, changing the conclusions.

B. Multivariate analysis

We proceed with the multivariate cross-sectional analysis of the trends in firm characteristics versus trends in idiosyncratic risk. The advantage of this approach is that now we can derive the **conditional** influence of every variable on the probability of observing a trend in risk, i.e. the influence of each characteristic holding other variables constant.

Table B.4 reports the results of multinomial logit regressions of the dummy for trends in idiosyncratic risk on the dummies for trends in each of the characteristics. The test specifics are the following. The dependent variable takes the values +1,0, or -1 depending on whether a positive, insignificant, or negative trend is observed in the idiosyncratic risk during the life of the security. The base case in no trend, therefore we consider a model of two equations for the probabilities of trends in risk: one for the ratio of probabilities of positive versus insignificant trend, and one for the ratio of probabilities of negative versus insignificant trend. Each of the characteristics is assigned two dummy variables: one that takes the value 1 if a positive significant trend is observed and 0 otherwise, and one that takes the value 1 if negative trend is observed and 0 otherwise.[2]

Let us discuss in turn fundamentals, institutional ownership, and speculative trading hypothesis.

1. **Results on fundamentals** suggest that firms with increasing idiosyncratic risk are deteriorating in quality, while firms with decreasing idiosyncratic risk are improving in quality. For example, according to Table B.4 a growing firm is more likely to have a decreasing risk, while a firm with a decreasing total market value (possibly in distress) is more likely to have an increasing idiosyncratic risk (all size coefficients are significant at least at 1 %).

   Earnings and and **their volatility** are significant in these regressions (in contrast to the univariate analysis, possibly because some other firm characteristics obscure their influence in the unconditional distribution). Firms with continuously increasing **earnings per share** are likely to have a negative trend in idiosyncratic risk and are unlikely to have a positive trend. The opposite holds for the companies with decreasing earnings per share (all coefficients are significant at 1 %). Increasing volatility of earnings implies higher probability of observing an increasing idiosyncratic risk and a lower probability of observing a decreasing risk. The evidence on earning and their volatility is consistent

[2] We define two dummies (instead of one) for the firm characteristics since we do not wish to assume that the coefficients on positive and on negative trend are equal or related. Therefore in our model the influence of say positive trend in a firm characteristic can be different from the influence of the negative trend in this characteristic. The reported standard errors are robust to the presence of heteroskedastisity.

with the findings in Wei and Zhang (2006) (among others), which indicate that idiosyncratic risk and earnings are negatively related, while idiosyncratic risk and volatility of earnings are positively related.

Firms with increasing book-to-market are less likely to have a decreasing idiosyncratic risk. Increasing amount of available cash per dollar of the firms' assets implies a larger probability of a positive trend and a smaller probability of a negative trend in the firm's idiosyncratic volatility. The opposite is true for the negative trend in cash ratio. More available cash in this case may be associated with an increasing risk of equity returns since managers of the firms with higher risk tend to hold more cash. Firms with a growing leverage ratio are more likely to have an increasing risk. Decreasing leverage ratio diminish the probability of a negative trend in risk, but does not affect that of a positive trend. Additionally, firms with a positive trend in returns are less likely to have an increasing idiosyncratic risk, while those with negative trend in returns are more likely to have increasing risk. Finally any trend (positive or negative) in R&D is likely to reduce probability of a negative trend in risk.

Therefore our results suggest that firms with increasing idiosyncratic risk are also likely to diminish in size and returns, have decreasing earnings along with increasing earnings' volatility, leverage, and cash ratio. Conversely, companies which have decreasing idiosyncratic risk are more likely to grow in value, returns and earnings, have decreasing volatility of earnings, leverage, and cash.

2. **Institutional ownership** as well has an effect on the probability of trends in risk. A growing ownership share of institutions implies we are less likely to observe an increasing idiosyncratic risk and more likely to observe a decreasing risk. A decreasing share of institutions implies a higher probability of a positive trend in risk, but does not affect probability of a negative tend. Therefore

institutions seem to abstract from securities with an increasing risk. This is contrary to what was suggested in Malkiel and Xu (2003), i.e. increasing average idiosyncratic risk in the US markets is due to the growing average institutional ownership share, and in correspondence with the suggestions in Brandt, Brav, and Graham (2005) that larger institutional ownership share may imply lower idiosyncratic risk.

In order to trace the difference of our results from those of Wei and Zhang (2006) we repeat their panel regressions on our sample. The original regression in Wei and Zhang (2006) determines the effects of size and institutional ownership on idiosyncratic risk. The estimates of their model on our sample are the following:

$$\begin{array}{llll} IR_{it} = 0.0044 & -0.0006\ size_{it} & +0.0002\, ins_{it} \\ & (-46.45) & (1.83) \end{array}$$

In this paper we use more control variables then Wei and Zhang (2006). As it turns out adding some of them to the regression changes the sign of the coefficient on institutional ownership. Specifically, adding earnings per share or volatility of earnings does not have an effect, but book-to-market, cash ratio, leverage, turnover, or research and development does. The regression results for the full set of controls are the following:

$$\begin{array}{llll} IR_{it} = 0.0043 & -0.0005 * size_{it} & -0.0021 * ins_{it} & \\ & (-32.34) & (-19.47) & \\ -0.0003 * eps_{it} & -1.13 * 10^{-5} * veps_{it} & +0.0003 * bm_{it} & +0.0006 * cashr_{it} \\ (-6.42) & (-0.31) & (8.21) & (6.77) \\ -0.0009 * lev_{it} & +0.0018 * turn_{it} & +0.0147 * rnd_{it} & \\ (-7.81) & (28.73) & (21.53) & \end{array}$$

As we can see the ownership appears with significant negative sign in the last regression. This result also highlights importance of multivariate versus univariate analysis for this issue.

3. **Speculative trading**. Brandt, Brav, and Graham (2005) propose that the increasing market average idiosyncratic risk could be due to speculative trading

in low-priced stocks. In our context this implies that if a security is becoming cheaper we should observe an increasing idiosyncratic risk as more speculators are attracted to this stock. Therefore a negative trend in security's price should correspond to a positive trend in its risk. At the same time since more speculators are being attracted, the security's turnover should increase, causing a larger volatility.

Estimated regression coefficients on **price dummy** confirm this conjecture. Negative trend in price is likely to increase probability of a positive trend in risk and decrease probability of a negative trend. Positive trend in price has the opposite effect on trends in risk. The evidence on the **turnover ratio** though is not in agreement with this intuition. Positive trend in turnover increases probability of a negative trend in idiosyncratic volatility while its effect on appearance of a positive trend is insignificant.

We repeat our analysis with either price dummy or turnover dummy excluded from the regression (third and forth models in table B.3) to account for the possibility that a relationship between these two variables cause the effect or either one appear insignificant or change the sign. This manipulation does not affect any of our previous conclusions, which are therefore robust.

As can be concluded from the panel regression of idiosyncratic risk on our main characteristics turnover enters with the positive sign, as indicated in Brandt, Brav, and Graham (2005) (results not reported). This regression though and the multinomial logit model may give apparently contradicting results since they show different effects: short-run (panel regression) and long-run (multivariate logit) changes in idiosyncratic risk. Our first-stage trend estimation implies that:

$$\Delta IR_{it} = \alpha_1^i \Delta t + \Delta e_{it}^{IR} \tag{2.4}$$

$$\Delta turn_{it} = \gamma_1^i \Delta t + \Delta e_{it}^{turn} \tag{2.5}$$

In terms of the panel regression the effect of changes in turnover on changes in idiosyncratic risk is the following (assuming $\Delta t = 1$):

$$\frac{\Delta IR_{it}}{\Delta turn_{it}} = \frac{\alpha_1^i + \Delta e_{it}^{IR}}{\gamma_1^i + \Delta e_{it}^{turn}} \tag{2.6}$$

This ratio combines the effect of the difference in signs of trend coefficients (α_1^i and γ_1^i) and the effect of short-run deviations around the trends (Δe_{it}^{IR} and Δe_{it}^{turn}). In our sample the second effect is much larger than the first since estimated tend coefficients in the first stage are very small in magnitude. We are specifically interested though in the long-run effect since we want to be able to explain appearance of trends in idiosyncratic risk of securities, not per-period changes in idiosyncratic risk. Therefore our tests do not contradict evidence in Brandt, Brav, and Graham (2005), just address a different research question.

So far we have seen that the trend in the price is related to the trend in idiosyncratic risk, but the nature or causality of this relationship is not quite clear. Speculative trading in cheap stocks is not a likely reason since the effect of lowering the price on risk should be transmitted via an increased frequency of trading, which is not observed in our sample. Security prices, like firm's size, can measure effects of various economic factors. Given our evidence we cannot yet definitely conclude which one is at play.

Altogether the evidence shows that well performing companies, which are increasing in the total market value, have growing earnings and decreasing earnings' volatility and decreasing leverage, are more likely to have a decreasing idiosyncratic risk. The opposite holds for the firms which are not doing as well (decreasing in size and returns, have increasing leverage). Institutional owners tend to increase their share in the first type of companies and decrease in the second. Not surprisingly, the stock price of the first type is likely to increase, while of the second - to decrease. It is not at all clear therefore whether the idiosyncratic risk is increasing due to a decreasing price or the other way around. A third plausible possibility is that risk and price are related to some other variables which cause appearance of a statistical relationship between the two.

As we discussed in the previous section, some market wide factors could as well be driving the changes in the idiosyncratic risks of securities, either via fundamentals or in addition to their influence. While institutional ownership and speculative trading seem less likely to be the major factors.

2.3.2 Robustness checks

We would like to conduct several robustness checks of our conclusions. For this purpose we divide our sample into several sub-samples (Table B.5). Specifically, we perform our multinomial logit regressions on samples of high-priced and low-priced securities, on CLMX and Post-CLMX period, securities with long and short life, and securities that were listed before 1997 and afterwords.

1. The first split of the sample is necessary as some authors showed (for example Brandt, Brav, and Graham (2005)) that influence of institutional ownership on idiosyncratic risk is different for high-priced and low-priced stocks. The coefficients on other characteristics may be sensitive as well to the price level of security. We define security to be a low-price if in 70 % of the observations its (inflation-adjusted) price is above 5 dollar level (also adjusted by current inflation level). and low-price otherwise.

   The results are the first two columns in Table B.5. As the estimates indicate, the effect of trends in institutional ownership share on probabilities of trends in idiosyncratic risk does not depend on whether the stock is high-price or low-price. Coefficient magnitudes and significance levels do not change much if we split the sample according to price. Book-to-market, leverage and volatility of earnings change significance levels in some cases, while size and cash ratio change significance and sign.

2. We also want to make sure that our results are unaffected by the fact that we combine CLMX and post-CLMX periods. We split our sample into the two sub-samples and compare the resulted estimates to the original regression (models three and four in Table B.5).

   Several coefficients have changed the significance in the resulting sub-samples. Earnings, earnings volatility and size coefficients seem to be non-robust to this split. For instance, in the post-CLMX period increasing size corresponds to a lower probability of observing negative trend in risk, while in the total and CLMX samples the relationship is the opposite. Similarly increasing volatility of earnings corresponds to a lower probability of observing a positive trend in idiosyncratic risk during CLMX period, while the opposite is true for the total and post-CLMX samples. This analysis suggests that such measures of firm fundamentals as earning per share, earnings volatility, and size may not have a stable (in time) relationship with firm-specific risk.

   Additionally we need to address the problem of unbalanced panel in our sample. Different companies in our cross-section are first listed at different times: some in early 60s, others in the recent years. Such firms could be quite different. Therefore we divide our sample into two groups: securities first listed in or before 1998 and those originally listed afterwords. Also various companies have different life spans: some existed for one-two years, others for ten years or more. To account for this difference we divide the total sample into two groups according to life span: those, which existed for less than ten years and those that existed longer. The results are presented in the last two models in Table B.5.

3. When the sample is split according to the **security listing date** no major differences can be detected in the regression estimates. Several variables changed the significance levels in some places: cash ratio, book-to-market, earnings, size, leverage, turnover, price, and return. Dummy for positive trend in institutional ownership changed the sign in the equation for the probability of trend in idiosyncratic risk.

4. Even fewer differences compared to the original estimates are observed when the sample is split according to the **life spans** of securities. Cash ratio, institutional ownership, leverage, size, return, and earnings volatility change significance of the coefficients in some places. Dummy for positive trend in earnings changes the sign (to negative) in the equation for the probability of positive trend in idiosyncratic risk.

2.3.3 Explaining magnitudes of trend coefficients

Motivation and tests description

So far we have focused our investigation on the question of how appearance of trends in firm characteristics affects the probability of observing a trend in the firm-specific risk. In other words, our research question was: is there a long-term relationship across firms between risk and firm characteristics and what is its direction. Now let us ask a question whether the strength of this effect is similar across securities. If so, the effect of the company's characteristics will also show up in the **magnitudes** of the estimated trend coefficients. For example, a stronger trend in earnings may imply a stronger trend in idiosyncratic risk in addition to the fact that an *existing* trend in earnings implies existence of an opposite trend in volatility. In this example cross-sectional association between trend magnitudes means that not only decreasing earnings of a firm imply increasing volatility, but also that the strength of this relationship is similar across firms. If on the other hand no relationship between trend coefficient magnitudes can be found, idiosyncratic risk and earnings are oppositely related, but the relationship coefficient can be different in magnitude across firms.

To address this question we regress the trend coefficient on risk on the coefficients on trends in firm characteristics. Results are summarized in Table B.6. We consider three cases: least squares regression of the trend coefficients (regardless of their signs or significance levels in the first stage, model 1); Tobit regression of the sample of positive significant (at least at 5 % level) trend coefficients of idiosyncratic risk as a dependent variable (model 2); and Tobit regression of negative significant trend coefficients of idiosyncratic risk (model 3).

Estimation results

Only two fundamental variables appear as robustly significant explanatory factors for the magnitudes of trends in idiosyncratic risk: size and earnings' volatility. Trend coefficient on **size** has a significant diminishing effect on the trend coefficient on idiosyncratic risk, i.e. more quickly growing companies have a slower decreasing risk. If the firm has faster diminishing total market value (possibly in distress) its idiosyncratic risk also increases at a faster rate.

Coefficient on trend in **volatility of earnings** affects coefficient on trend in risk only in the case of the negatively trending (risk) securities. According to the estimation results, a higher rate of decrease of earnings' volatility corresponds to a faster decreasing firm-specific risk.

These results further confirm our "'quality"' hypothesis; i.e. decreasing idiosyncratic risk firms are increasing in quality and vise versa. The strength of this relationship is quite random across firms, with the exception of size and earnings' volatility, for which we can reasonably well predict what firm should have a stronger relationship.

Based on our overall evidence in this section we conclude that

- The firms with increasing idiosyncratic risk are more likely to be distressed or otherwise not performing well on the market, while the the firms with decreasing idiosyncratic risk are characterized by improving performance.

- Trends in the stock price should reflect this fact and therefore it is not clear whether speculative trading plays a role in the relationship between price and firm-specific risk.

- The fundamentals like earnings and their volatility are good indicators of the firms' condition and therefore are good predictors of the trends in risk.

- Institutional owners may prefer well performing companies and thus their relationship with the idiosyncratic risk may be via the relationship with the firms' fundamentals and not directly related to idiosyncratic risk.

2.4 Conclusions and discussion

This paper investigates appearance of trends in idiosyncratic risk at the security level. Current research in the area concentrated on the explanations of the trend in the economy average idiosyncratic risk. Lumping all firms together though may leave out some important properties of the trend. We investigate these properties in the firm-by-firm trend estimation and the effects on the average idiosyncratic risk as well as portfolio implications for investors.

Our results indicate that

- New lists cannot fully account for the observable patterns in the average idiosyncratic risk on US market. The trend behavior of idiosyncratic risk differs from security to security. About 30% of the existing stocks have positive trends and about 20% have negative trends.

- Changing (in time) proportions of the two groups result in stronger influence of one group on the market average idiosyncratic risk. This induces fluctuations of the average risk around its trend line.

- Trends in firm's fundamentals affect the appearance of trends in idiosyncratic risk. In agreement with the current literature negative trend in earnings and positive trend in earnings' volatility correspond to a positive trend in risk.

- Contrary to suggestions in the literature increasing institutional ownership corresponds to a *decreasing* idiosyncratic risk. According to our evidence the difference in results stems from a model misspecification problem, which we attempt to correct.

- In agreement with the literature an increasing (real) stock price implies a negative trend in idiosyncratic risk. Our analysis of turnover though indicates it has a negative long-run relationship with risk. This result does not support the proposed in the literature hypothesis that increases in idiosyncratic volatility are due to bursts of speculation in the low-priced stocks.

The results of this paper suggest that idiosyncratic risk of individual security has a non-trivial relationship with its fundamental variables. This of course is not counter intuitive and in fact should be anticipated. What seems strange is why should this effect persist in time? In other words, if firms with increasing risk are deteriorating in performance, why are they not being delisted or at least forced by the capital market to improve performance? We propose (but do not investigate) a few possibilities in this regard:

1. The literature suggests that financial markets are becoming less restrictive in standards for the listed securities (see for example Fama(04)). It is being argued that newly listed companies are allowed to be less profitable and to have more volatile cash flows. On the other hand, the same market conditions should allow existing firms to lower their performance standards (and use less managerial effort), which would lead to the upward trends in their risk. This argument though brings up a different question: why does the market lower its standards? Is there increasingly more available capital to invest so it is hard to find best use for all of it? Or is there something about investors' psychology? These or other possibilities can make an interesting topic for future research.

2. As the data suggests the number of securities has increased dramatically since early 60s. If the number of investors have not significantly changed, less investor attention can be devoted to each security. This could mean worse capital market supervision and worse performance. The investors can be compensated for such losses via increased diversification benefits.

3. The observed relationships could also be the result of measurement or modeling issues. The market model is a static relationship. If the relationship is in fact dynamic, faster speed of market adjustments can lead to our inability to spot the static equilibrium.

CHAPTER 3

On causality of the relationship between institutional ownership and idiosyncratic risk

3.1 Introduction

Idiosyncratic volatility has experienced growing interest in the finance literature since a study by Campbell, Lettau, Malkiel, and Xu (2001), which showed presence of a significant trend in the market average firm-specific risk. Subsequent research investigated the causes as well as the consequences of these changes in idiosyncratic volatility. Among numerous suggested drivers behind idiosyncratic risk is institutional ownership, initially advocated by Malkiel and Xu (2003). The authors rely on the observed positive trend in institutional ownership, similar to the one found in average idiosyncratic risk. They propose the following reasoning for the existence of such a relationship (p. 636): "...buying and selling is more likely to be coordinated across institutions, and market prices may be more volatile and more quickly responsive to new information or to changes in risk perceptions". Their cross-sectional regression analysis confirms this intuition in that institutional ownership is positively associated with idiosyncratic risk.

Several studies that followed investigated further this relationship. Thus, Dennis and Strickland (2005) show Malkiel and Xu (2003)'s results to be robust to inclusion of leverage and firm focus as other potential explanatory variables. Chang and Dong (2005) investigate how institutional herding (measured as changes in institutional ownership) affect idiosyncratic volatility and find a similar significant relationship. Brandt, Brav, and Graham (2005) on the other hand show that the relationship, although it retains its significance, has a reversed sign in the sub-sample of high-priced securities. Vozlioublennaia (2006) shows that the sign of the relationship in the pooled regression is sensitive to the inclusion of some firm characteristics.

Even though the sign of the relationship may be somewhat illusive, its significance seems to be established in empirical literature. The question remains though whether it is institutional ownership that is causing changes in idiosyncratic risk and not the other way around. A number of studies (theoretical and empirical) suggest this other possibility. A model of incomplete information by Merton (1987), for example, implies that firm managers tend to expand the investor base if idiosyncratic risk is increasing. This happens because investors are forced to hold part of idiosyncratic volatility in their portfolios due to incomplete information. As a result, firms may want to increase the number of informed (about their securities) investors, thereby reducing the incomplete information effect and avoiding paying a higher premium for larger idiosyncratic volatility. Since institutional investors may be better able to collect and process information about stocks, this implies increasing institutional ownership share. Alternatively, if managers choose to pay higher premiums for larger idiosyncratic risk, institutional owners being at advantage in collecting information and diversification will rationally buy stocks with high idiosyncratic risk and extract profits. In either scenario, changes in idiosyncratic volatility cause changes in institutional ownership. In fact, some studies (e.g., Boehme, Danielsen, Kumar, and Sorescu (2005) and Kelly (2005)) use institutional ownership as a proxy for investor attention received by a firm, in line with Merton (1987) and our intuition. Furthermore, Falkenstein (1996) empirically confirms that institutional owners tend to hold securities with larger idiosyncratic risk.

Chang and Dong (2005) examine the possibility of reversed causality and its effect on their results, and find (in a pooled regression setting) it to be negligible. We address this issue in a time-series set-up, i.e., a Vector Error Correction Model (VECM). This allows us not only to test directly for causality, but also to account for non-stationarity of the variables of interest. Our results show that there is indeed a cointegrating relationship between (detrended) market average institutional ownership and idiosyncratic risk, and changes in idiosyncratic risk can sometimes induce changes in institutional ownership, i.e. endogeniety is present in the relationship. Furthermore, we show that the effect of institutional ownership on idiosyncratic risk, though statistically significant, can be considered negligible for all practical purposes. Our estimates predict that it would take over hundred years to incorporate this effect. Additionally, we detect a structural shift in the long-run relationship of institutional ownership and risk around second quarter of 2000. We suggest it was caused by the Technological Bubble burst in March 2000.

Our testing method allows us to address directly the causality question in time-series set-up. This approach determines why a variable such as, for example, idiosyncratic risk changes from period to period, not why it differs from security to security (as in cross-sectional set-up). The pooled regression analysis would make it impossible to separate the two effects.

The dynamics of idiosyncratic risk is an important research topic as some previous studies suggest that it may be priced (Ang, Hodrick, Xing, and Zhang (2006), Goyal and Santa-Clara (2001), among others). These papers show that past values of idiosyncratic risk may help predict future returns. Many of these studies though use pooled estimation set-up and therefore do not distinguish between cross-sectional and time-series drivers of the relationship. In addition, the fact that idiosyncratic risk may be non-stationary makes the results of such analysis even more questionable.

3.2 Data, test construction, and main result

In this section we establish the main result for the relationship between average institutional ownership and idiosyncratic risk. First, we would like to confirm that a significant relationship exists in time series set-up, after which we proceed with causality analysis.

Our data come from CRSP (security returns) and 13(F) filings (institutional ownership) databases. We consider period from January 1980 till December 2004. Since firm characteristics are measured quarterly, we use the same frequency for other variables. Our measure of idiosyncratic risk is constructed as the end of the quarter average monthly variance of the Fama and French three factor model residual. The model is estimated for each month on the daily return data:

$$(r_{it} - r_{ft}) = \alpha_i + \beta_i(r_{mt} - r_{ft}) + \beta_{1i} smb_t + \beta_{2i} hml_t + e_{it}, \tag{3.1}$$

$$IRFF_{it} = \frac{1}{t}\sum_{s=1}^{t} e_{is}, \tag{3.2}$$

where IRFF is our measure of idiosyncratic risk, r_{it} is return of stock i in period t, r_{mt} is the market return, r_{ft} is the risk-free rate, smb_t and hml_t are the Fama and French two factor portfolios (obtained from K. French's web page). We require for statistical accuracy at least ten daily return observations for each firm in a given month. We then find simple market average for both idiosyncratic risk and institutional ownership share. Next, we detrend both of these variables and use the residuals from the following equations:

$$IRFF_{it} = \alpha_{i1} + \beta_{i1} t + e_{it1}. \tag{3.3}$$

$$INS_{it} = \alpha_{i2} + \beta_{i2}t + e_{it2}, \tag{3.4}$$

where INS is average institutional ownership. Since stationarity issues play a significant role in time series analysis, we first check our variables for the presence of the unit root. Table C.1 reports the results of the Augmented Dicker-Fuller tests and confirms non-stationarity of both institutional ownership and idiosyncratic risk. Therefore, the two variables must be cointegrated if they are related. The Johansen Cointegration Test confirms this conjecture. We apply the Johansen method (Johansen (1991) and Johansen (1995)). The specification we use allows the series to have linear trends. The likelihood ratio trace statistic is computed as follows:

$$Q_0 = -T \sum_{i=0}^{1} log(1 - \lambda_i), \tag{3.5}$$

where λ_i is the i-th largest eigenvalue. It is the test of H(0), no cointegrating equations, against H(1), one cointegrating equation. The critical values for the test are taken from Osterwald-Lenum (1992).

We first run a rolling estimation of the relationship (Table C.2) to check for the possibility of structural changes. This step is dictated by the trajectory of idiosyncratic risk, which was gradually increasing until 2000 and fell abruptly afterward. We suspect the Technological Bubble burst of March 2000 may be responsible for shifts in the behavior of idiosyncratic risk as well as its relationship with institutional ownership.

The results of the rolling estimates show the relationship looses significance in the recent years. Following our intuition regarding the Bubble we add a dummy variable to the relationship, which takes the value one for all the observations starting from the second quarter of 2000. Thus we allow the intercept (but not the coefficient) of the relationship to change after the Technological Bubble. As it turns out including this dummy renders the relationship significant in the whole sample (including recent years). The likelihood ratio statistic for the two variables is 34.67, while 5%(1%) critical values are 29.68(35.65). Therefore, we reject at 5% the hypothesis of no cointegration between average institutional ownership and idiosyncratic risk. We will keep the dummy variable in the equation for the remaning tests of the long-run relationship.

Our next step is to check for short-run causality between ownership and risk. We will use Granger Causality tests for this purpose. We employ the following two-lag model:

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \beta_1 y_{t-1} + \beta_2 y_{t-2} \tag{3.6}$$

to test whether y Granger-causes x. It is the Wold test for the joint hypothesis $\beta_1 = \beta_2 = 0$, i.e. y does not cause x. The p-value for null hypothesis "institutional ownership does not Granger Cause idiosyncratic risk" is 0.61. We therefore unable to reject it at any conventional level. The p-value for the opposite hypothesis, i.e. "idiosyncratic risk does not Granger Cause institutional ownership", is 0.18. Therefore, we can state that the variables are unrelated in the short run.

We will now proceed to investigation of the causality in the long-run using VECM. We estimate the following model:

$$\Delta IRFF_t = \varphi_{01} + \varphi_{11} ECT_{t-1}$$

$$+\varphi_{12}\Delta IRFF_{t-1} + \varphi_{13}\Delta IRFF_{t-2} + \varphi_{14}\Delta INS_{t-1} + \varphi_{15}\Delta INS_{t-2}, \tag{3.7}$$

and

$$\Delta INS_t = \varphi_{02} + \varphi_{21} ECT_{t-1}$$

$$+\varphi_{22}\Delta IRFF_{t-1} + \varphi_{23}\Delta IRFF_{t-2} + \varphi_{24}\Delta INS_{t-1} + \varphi_{25}\Delta INS_{t-2}, \tag{3.8}$$

where $ECT_t = \alpha_0 + INS_t - \alpha_1 IRFF_t - \alpha_2 D00_t$, $D00$ is the dummy for observations starting with the second quarter of 2000. We are interested in the significance of the coefficients on the error correction term (ECT) in each equation: φ_{11} and φ_{21}. If both of them are significant the causality runs in two directions. If one is significant and the other one is not, we can clearly determine which variable is endogenous (the one with significant coefficient) and which one is exogenous (the one with insignificant coefficient).

The estimation results for the above model are summarized in Table C.3. ECT is estimated as $ECT_t = 0.06 + INS_t - 141.95 * IRFF_t - 0.31 * D00_t$ (the residual from the regression of ownership on risk and the dummy). The coefficients on error correction term confirm our intuition: φ_{21} is significant, indicating that idiosyncratic risk affects institutional ownership. Since φ_{11} is significant as well the evidence suggests that causality runs in both directions. But before we reach a final conclusion regarding the causality in this relationship let us examine economic significance of these coefficients.

First, we note that coefficient on ECT in the dynamics of idiosyncratic risk is much smaller then that of institutional ownership. The two variables though have very different variances, which makes these coefficients not directly comparable. This concern can be addressed by computing half-life for both using the following formula: $ln(1/2)/ln(1 - \varphi_{i1})$. The half-life will tell us how many quarters it takes for a shock in ECT to be reduced in its effect on ownership or risk by half. In case of institutional ownership it is 43 quarters or almost 11 years. For idiosyncratic risk the estimate is 693 quarters or 173 years. We would like to point out that such slow effect can hardly be considered economically significant in a world of quickly adjusting stock prices and risk. The combined effect of short and long-run adjustments of institutional ownership and idiosyncratic risk to a single shock can be observed in figures 1 and 2. As these trajectories suggest it takes about 10 years for the system to reach the equilibrium. We conclude that changes in average idiosyncratic risk can potentially explain the raise in average institutional ownership while changes in ownership are unlikely to have an economically significant effect on idiosyncratic risk.

3.3 Future work

As a robustness check of these results we propose to repeat the above tests with alternative measures of idiosyncratic volatility. For instance, volatility can be measured as the residual of one-factor Market Model or the Market Model with other risk factors, such as momentum.

We ran the model estimation month-by-month for each security, different specifications (say, 5 years interval) can be considered as well, which may increase statistical accuracy of risk estimates (possibly in expense of betas' flexibility).

Malkiel and Xu (2003) used GARCH model as an alternative estimation technique, which can be incorporated in this analysis as well. Although GARCH imposes certain structure on the variance, it has been proved very successful in modeling variances of financial series.

Campbell, Lettau, Malkiel, and Xu (2001) proposed a technique, which allows to derive average market idiosyncratic risk without estimation of betas. This method assumes though no cross-correlation of betas, which their paper shows to be a minor issue.

Another test of robustness would be an addition of several control variables used in related literature: average firm's earnings per share, volatility of earnings, turnover, size, leverage and book-to-market. Earnings per share and their volatility were proposed by Wei and Zhang (2006) and Irvine and Pontiff (2005) as potential fundamental explanatory variables for idiosyncratic risk. Size was included as a control factor along with institutional ownership by Malkiel and Xu (2003). Brandt, Brav, and Graham (2005) consider turnover as an important variable in explanation of the behavior of idiosyncratic volatility, which they claim is a proxy for speculative trading. Leverage, measured as the ratio of the book value of debt to total assets, was included by Dennis and Strickland (2005). Book values though are slow to adjust following rapid changes of the market, therefore we propose as well an alternative measure of leverage based on the market values. This variable may serve as a better explanatory factor for risk.

To test if a given control is responsible for the appearance of the relationship between institutional ownership and risk we propose first to run cointegration test for the system of four variables: ownership, risk, dummy for the observations after the first quarter of 2000, and a control. If cointegration is established we can further test robustness of our results in the following VECM:

$$\Delta IRFF_t = \varphi_{10} + \varphi_{11} ECT_{1t-1} + \varphi_{12} ECT_{2t-1} + \varphi_{13} \Delta IRFF_{t-1} + \varphi_{14} \Delta IRFF_{t-2}$$

$$+\varphi_{15} \Delta INS_{t-1} + \varphi_{16} \Delta INS_{t-2} + \varphi_{17} \Delta CONTROL_{t-1} + \varphi_{18} \Delta CONTROL_{t-2}, \quad (3.9)$$

and

$$\Delta INS_t = \varphi_{20} + \varphi_{21} ECT_{3t-1} + \varphi_{22} ECT_{4t-1} + \varphi_{23} \Delta IRFF_{t-1} + \varphi_{24} \Delta IRFF_{t-2}$$

$$+\varphi_{25} \Delta INS_{t-1} + \varphi_{26} \Delta INS_{t-2} + \varphi_{27} \Delta CONTROL_{t-1} + \varphi_{28} \Delta CONTROL_{t-2}, \quad (3.10)$$

where $ECT_{1t} = \alpha_{10} + INS_t - \alpha_{11} IRFF_t - \alpha_{12} D00_t$,

$ECT_{2t} = \beta_{10} + CONTROL_t - \beta_{11} IRFF_t - \beta_{12} D00_t$,

$ECT_{3t} = \alpha_{20} + IRFF_t - \alpha_{21} INS_t - \alpha_{22} D00_t$,

$ECT_{4t} = \beta_{20} + CONTROL_t - \beta_{21} INS_t - \beta_{22} D00_t$.

The idea behind this set up is the following. We want to be able to determine pair-wise relationships among the three variables: ownership, risk and control. The question we ask here is whether institutional ownership adjusts to risk in equilibrium even after its equilibrium relationship with control has been accounted for (ECT_2). Same holds for idiosyncratic risk. We still expect to find that φ_{21} is significant even after deviations from equilibrium with control (terms ECT_2 and ECT_4) have been added to the system.

One may consider as well a firm-level analysis of the specified relationship in a sample of, say, 30 Dow Jones Industrial Average Index securities to test how the conclusions stand outside the market averages. Same can be done for the portfolios of securities sorted by size or book-to-market and weighted by market capitalization. Such a procedure is shown to reduce considerably the noise.

Finally, investigating the relationship for the possibility of non-linearity is another possible avenue for future research of this topic.

APPENDIX A

Tables and Figures for Essay 1

Table A.1. **Descriptive statistics**

This table reports major statistical indicators for the variables of interest. All series are in logarithms. LIRCV is the CLMX idiosyncratic risk measure constructed using the value-weighted market index, LIRCE is the CLMX idiosyncratic risk measure constructed using the equally-weighted market index, LIR is idiosyncratic risk constructed using the simple Market Model, LIR5Y is idiosyncratic risk constructed using the simple Market Model regressions by 5 year intervals, LIRFF is idiosyncratic risk constructed using the Market Model with Fama-French factors, LIS is idiosyncratic volatility of sales, LICF is idiosyncratic volatility of cash flows, and LIE is idiosyncratic volatility of earnings. γ_t is the log of Quasi-Herfindahl Index. LNS is the total number of securities in the market. Sample size for all the variables is 498.

Variables	LIRCV	LIRCE	LIR	LIR5Y	LIRFF	LIS	LICF	LIE	γ_t	LNS
mean	-6.5429	-6.5561	-6.5195	-6.5567	-6.5644	2.7010	-0.6635	4.1464	-5.0134	8.5476
median	-6.6429	-6.6634	-6.6545	-6.6564	-6.6682	2.2817	-1.0040	4.1570	-5.1245	8.7496
maximum	-4.9816	-4.9984	-5.0060	-5.0215	-5.0339	7.0935	5.5298	12.5329	-3.6089	9.1284
minimum	-7.6146	-7.6292	-7.6115	-7.6348	-7.6406	1.3585	-3.1832	0.8304	-5.8782	7.6377
st.dev.	0.5999	0.5991	0.5964	0.5969	0.5969	1.2340	1.9674	1.8507	0.5864	0.4785
skewness	0.3622	0.3696	0.3593	0.3588	0.3618	1.8374	0.9901	1.0380	0.2934	-0.8611

Table A.2. **Correlation matrix**

This table reports correlation coefficients for major variables.

Variables	LIRCV	LIRCE	LIR	LIR5Y	LIRFF	LIS	LICF	LIE	γ_t	LNS
LIRCV	1.0000	0.9998	0.9999	0.9997	0.9993	0.3544	0.5702	0.6243	-0.6808	0.7631
LIRCE		1.0000	0.9999	0.9998	0.9998	0.3554	0.5698	0.6257	-0.6847	0.7628
LIR			1.0000	0.9999	0.9996	0.3541	0.5709	0.6256	-0.6842	0.7651
LIR5Y				1.0000	0.9997	0.3519	0.5700	0.6251	-0.6852	0.7662
LIRFF					1.0000	0.3532	0.5698	0.6260	-0.6891	0.7657
LIS						1.0000	0.7176	0.7532	-0.2698	0.4310
LICF							1.0000	0.7568	-0.3760	0.7134
LIE								1.0000	-0.5680	0.7178
γ_t									1.0000	-0.6798
LNS										1.0000

Table A.3. **Augmented Dickey-Fuller unit root tests**

This table reports results of Augmented Dichey-Fuller tests for major variables. All tests include four lags. other specifications provide similar results and are available upon request. MacKinnon critical values are equal -3.4459 for the 1% level and -2.8677 for the 5% level. The null hypothesis is the unit root in the data.

Variables	ADF statistic
LIRCV	-2.3771
LIRCE	-2.3461
LIR	-2.3706
LIR5Y	-2.3826
LIRFF	-2.3284
LIS	-2.7401
LICF	-3.0162
LIE	-1.8641
γ_t	-1.3962
LNS	-1.8538

Table A.4. **Johansen cointegration tests**

This table reports the results of Johansen cointegration tests for the five measures of firm-specific risk. In these tests each measure of idiosyncratic risk is paired with γ_t . Specifications allows for a linear deterministic trend in the data. Critical values are obtained from Osterwald-Lenum (1992) and are equal to 20.04 (1%) and 15.41 (5%). * indicates rejection of the null of no cointegrating equations at the 5% level.

Idiosyncratic risk measures	Likelihood ratio statistic
LIRCV	17.41*
LIRCE	17.26*
LIR	17.21*
LIR5Y	17.23*
LIRFF	17.14*

Table A.5. **Estimated cointegrating coefficients**

This table reports estimated coefficients in cointegrating equation for each of the measures of firm-specific risk. The normalization variable is idiosyncratic volatility, which coefficient is set equal to 1.

Idiosyncratic risk measures	Constant	γ_t
LIRCV	10.2915	0.7481
LIRCE	10.3257	0.7523
LIR	10.2940	0.7473
LIR5Y	10.3038	0.7478
LIRFF	10.3445	0.7544

Table A.6. **VEC model for various measures of idiosyncratic risk**

This table reports estimated VECM for various measures of idiosyncratic risk. ECT is the error correction term. DV is the dependent variable. LIR* is the appropriate measure of idiosyncratic risk. t statistics are given in parentheses.

IR measure	LIRCV		LIRCE		LIR		LIR5Y		LIRFF	
DV	Δ LIRCV	$\Delta\ \gamma_t$	Δ LIRCE	$\Delta\ \gamma_t$	Δ LIR	$\Delta\ \gamma_t$	Δ LIR5Y	$\Delta\ \gamma_t$	Δ LIRFF	$\Delta\ \gamma_t$
Constant	0.0013	-0.0036	0.0013	-0.0035	0.0012	-0.0036	0.0012	-0.0036	0.0013	-0.0036
	(0.1466)	(-0.8503)	(0.1503)	(-0.8506)	(0.1478)	(-0.8502)	(0.1475)	(-0.8502)	(0.1547)	(-0.8505)
ECT	-0.0862	-0.0053	-0.0842	-0.0053	-0.0855	-0.0054	-0.0840	-0.0052	-0.0815	-0.0052
	(-4.2089)	(-0.5271)	(-4.1657)	(-0.5237)	(-4.1981)	(-0.5308)	(-4.1635)	(-0.5076)	(-4.1134)	(-0.5134)
Δ LIR* lag1	-0.1662	0.0110	-0.1616	0.0122	-0.1562	0.0112	-0.1499	0.0106	-0.1478	0.0120
	(-3.6376)	(0.4896)	(-3.5385)	(0.5307)	(-3.4204)	(0.4892)	(-3.2859)	(0.4611)	(-3.2433)	(0.5118)
Δ LIR* lag2	-0.0560	-0.0069	-0.0580	-0.0086	-0.0597	-0.0063	-0.06256	-0.0076	-0.0612	-0.0093
	(-1.2417)	(-0.3109)	(-1.2876)	(-0.3801)	(-1.3246)	(-0.2788)	(-1.3876)	(-0.3316)	(-1.3587)	(-0.4000)
$\Delta\ \gamma_t$lag1	0.1484	-0.2784	0.1536	-0.2781	0.1427	-0.2782	0.1436	-0.2783	0.1565	-0.2780
	(1.6191)	(-6.1627)	(1.7076)	(-6.1584)	(1.5799)	(-6.1596)	(1.6052)	(-6.1609)	(1.7867)	(-6.1546)
$\Delta\ \gamma_t$lag2	0.1228	-0.1292	0.1257	-0.1295	0.1274	-0.1292	0.1253	-0.1294	0.1317	-0.1299
	(1.3430)	(-2.8670)	(0.4005)	(-2.8736)	(1.4150)	(-2.8680)	(1.4038)	(-2.8721)	(1.5067)	(-2.8807)
R-squared	0.0825	0.0794	0.0806	0.0796	0.0794	0.0793	0.0771	0.0793	0.0760	0.0795

Table A.7. **Cointegration tests with fundamentals**

This table reports estimates of Johansen cointegration tests with fundamentals. In these tests each measure of idiosyncratic fundamental volatility is combined with pairwise measures of idiosyncratic risk and γ_t . LR is the likelihood ratio statistic. **(*) indicates rejection of the null of no cointegrating equations at 1% (5%). 1% critical value is 20.04, 5% critical value is 15.41, and 10% critical value is 13.33.

Idios. fundamental volatility measures	LICF	LIS	LIE	LNS
LR for LIRCV	20.4999**	20.0327*	14.2305	19.8410*
LR for LIRCE	20.1612**	19.8750*	14.0748	19.3278*
LR for LIR	20.3141**	19.8612*	25.6331**	19.6528*
LR for LIR5Y	20.2935**	19.8707*	14.2560	19.4028*
LR for LIRFF	19.8322*	19.6132*	13.9562	19.0814*
LR for γ_t	13.3258	10.8058	9.1718	6.8854

Table A.8. **ADF unit root and Cointegration tests by industry**

This table reports estimates of ADF unit root and Johansen cointegration tests by industry. LIRCVi is industry i's CLMX measure of idiosyncratic risk. All variables are in logarithms. LR is cointegration test statistics with own γ_t and with market-wide γ_t. Critical values for the ADF test are -3.4459 (1%), and for the Cointegration test are 20.04 (1%), 15.41 (5%), and 13.33 (10%). * indicates failure to reject the unit root at 1%, rejection of no Cointegration at 5%; ** indicates rejection of no cointegration at 1%.

Industry	Idios.Risk	ADF stat.	γ_t^i	ADF stat	LR (γ_t^i)	LR (γ_t)
Agriculture	LIRCV1	-3.2544*	γ_t^1	-1.9599*	19.7413*	25.0024**
Food Products	LIRCV2	-2.7425*	γ_t^2	-0.9154*	20.8746**	23.1777**
Candy and Soda	LIRCV3	-5.1213	γ_t^3	-1.8455*		
Alcoholic Beverages	LIRCV4	-3.2816*	γ_t^4	-0.4669*	14.1080	22.5550**
Tobacco Products	LIRCV5	-5.1645	γ_t^5	-3.0989*		
Recreational Products	LIRCV6	-3.7541	γ_t^6	-2.9594*		
Entertainment	LIRCV7	-2.7614*	γ_t^7	-2.1821*	18.5267*	23.4248**
Printing and Publishing	LIRCV8	-2.7961*	γ_t^8	-2.4415*	22.5773**	19.2926*
Consumer Goods	LIRCV9	-3.1004*	γ_t^9	-1.5578*	12.6056	22.0305**
Apparel	LIRCV10	-2.8894*	γ_t^{10}	-1.5281*	15.2844	22.9108**
Health care	LIRCV11	-2.7148*	γ_t^{11}	-4.0331		
Medical Equipment	LIRCV12	-2.4015*	γ_t^{12}	-2.0532*	15.5659*	18.5034*
Pharmaceuticals	LIRCV13	-1.9612*	γ_t^{13}	-2.4034*	10.5335	12.0181
Chemicals	LIRCV14	-2.9772*	γ_t^{14}	-3.0276*	19.3288*	23.0888**
Rubber and Plastic	LIRCV15	-3.7735	γ_t^{15}	-2.5625*		

Table A.8. **Continued**

Industry	Idios.Risk	ADF stat.	γ_t^i	ADF stat.	LR (γ_t^i)	LR (γ_t)
Textiles	LIRCV16	-3.2971*	γ_t^{16}	0.7193*	17.9547*	19.4017*
Construction Materials	LIRCV17	-3.8534	γ_t^{17}	-1.4342*		
Construction	LIRCV18	-3.8391	γ_t^{18}	-2.1234*		
Steel Works	LIRCV19	-3.6200	γ_t^{19}	-1.9498*		
Fabricated Products	LIRCV20	-3.3675*	γ_t^{20}	-1.9850*	19.2054*	25.3202**
Machinery	LIRCV21	-2.5696*	γ_t^{21}	-2.9167*	15.2304	19.9582*
Electrical Equipment	LIRCV22	-2.6918*	γ_t^{22}	-2.8660*	16.2048*	19.4589*
Miscellaneous	LIRCV23	-3.8519	γ_t^{23}	-2.5994*		
Automobiles and Trucks	LIRCV24	-3.6288	γ_t^{24}	-1.6831*		
Aircraft	LIRCV25	-3.2822*	γ_t^{25}	-1.1743*	17.0173*	21.22.97**
Shipbuilding, Railroad Eq.	LIRCV26	-3.1210*	γ_t^{26}	-0.8816*	13.2633	17.1311*
Defense	LIRCV27	-3.6388	γ_t^{27}	-0.7999*		
Precious Metals	LIRCV28	-2.2823*	γ_t^{28}	-1.9758*	15.2195	11.2179
Nonmetallic Mining	LIRCV29	-2.6887*	γ_t^{29}	-2.7595*	16.4187*	18.0334*
Coal	LIRCV30	-3.4231*	γ_t^{30}	-0.7669*	12.7933	19.9761*
Petroleum and Natural Gas	LIRCV31	-2.5463*	γ_t^{31}	-1.2994*	13.6373	17.7780*
Utilities	LIRCV32	-2.0038*	γ_t^{32}	-0.5984*	7.3575	15.0182
Telecommunications	LIRCV33	-2.4935*	γ_t^{33}	-0.9934*	20.9314**	15.7011*
Personal Services	LIRCV34	-3.6696	γ_t^{34}	-2.2181*		
Business Services	LIRCV35	-2.5169*	γ_t^{35}	-2.0530*	15.7882*	20.1710**
Computers	LIRCV36	-2.5181*	γ_t^{36}	-0.9010*	17.3588*	18.1756*
Electronic Equipment	LIRCV37	-3.0445*	γ_t^{37}	-1.9206*	15.0323	25.0333**
Measuring and Control Eq.	LIRCV38	-2.4899*	γ_t^{38}	-2.5675*	25.0613**	19.0872*
Business Supplies	LIRCV39	-4.2395	γ_t^{39}	-1.3407*		
Shipping Containers	LIRCV40	-4.9577	γ_t^{40}	-1.7268*		
Transportation	LIRCV41	-2.9195*	γ_t^{41}	-2.7954*	16.3337*	22.8950**
Wholesale	LIRCV42	-2.9721*	γ_t^{42}	-2.6398*	20.4188**	25.8683**
Retail	LIRCV43	-2.4071*	γ_t^{43}	-1.6299*	14.8658	19.2374*
Restaurants, Hotel, Motel	LIRCV44	-2.9511*	γ_t^{44}	-2.0320*	17.6985*	21.2958**
Banking	LIRCV45	-2.6500*	γ_t^{45}	-1.7366*	11.4328	13.9035
Insurance	LIRCV46	-3.2097*	γ_t^{46}	-2.0409*	20.4611**	19.8902*
Real Estate	LIRCV47	-3.0345*	γ_t^{47}	-0.9277*	14.0977	15.1180
Trading	LIRCV48	-2.7504*	γ_t^{48}	-1.6783*	15.8643*	11.0495
The rest	LIRCV49	-3.3140*	γ_t^{49}	-2.2784*	17.9879*	17.8371*

Table A.9. **VECM and cointegrating equation coefficients by industry**

This table reports estimates of VECM and cointegrating equation coefficients for each industry. LIRCVi is industry i's CLMX measure of idiosyncratic risk. All variables are in logarithms. CE coef. is the estimated coefficient on market concentration in the cointegrating equation where idiosyncratic risk coefficient is normalized to -1. t stat.(1) is the t statistics on the error correction term in the equation for the changes in idiosyncratic risk as the dependent variable. t stat.(2) is the t statistics on the error correction term in the equation for changes in the market concentration as the dependent variable. *(**) indicates significance at least at the 5(1)% level.

Industry	γ_t			γ_t^i		
	CE coef.	t stat.(1)	t stat. (2)	CE coef.	t stat.(1)	t stat. (2)
Agriculture	-0.888	-5.78**	-0.65	0.510	-4.20**	1.99*
Food Products	-0.802	-4.90**	-0.57	1.798	-4.51**	2.37*
Alcoholic Beverages	-0.612	-5.28**	0.99			
Entertainment	-0.859	-5.32**	0.02	1.446	-3.95**	2.39*
Printing and Publishing	-0.588	-4.66**	0.38	-0.639	-4.13**	1.56
Consumer Goods	-0.529	-4.58**	0.46			
Apparel	-0.659	-4.91**	0.61			
Medical Equipment	-1.036	-4.26**	-0.64	-2.306	-3.22**	-1.37
Chemicals	-0.724	-5.47**	-0.62	2.192	-3.47**	2.15*
Textiles	-0.459	-4.70**	0.25	-0.016	-4.16**	2.44*
Fabricated Products	-0.882	-5.23**	-2.12*	0.348	-4.24**	1.01
Machinery	-0.829	-4.95**	-0.90			
Electrical Equipment	-0.774	-4.50**	-0.10	3.567	-3.34**	0.24
Aircraft	-0.441	-5.08**	1.19	0.926	-5.07**	0.30
Shipbuilding, Railroad Eq.	-0.815	-5.45**	-1.91			
Nonmetallic Mining	-0.986	-4.70**	-1.42	-1.754	-3.68**	-0.78
Coal	-0.723	-5.23**	-1.15			
Petroleum and Natural Gas	-0.811	-4.13**	-1.93			
Telecommunications	-1.042	-4.03**	-1.46	-0.693	-5.10**	-1.06
Business Services	-0.793	-4.49**	0.05	0.413	-3.29**	2.28*
Computers	-0.917	-4.36**	-0.14	-0.913	-4.20**	-1.93
Electronic Equipment	-0.665	-5.14**	-0.29			
Measuring and Control Eq.	-1.039	-4.32**	-0.92	-1.572	-2.53*	-3.61**
Transportation	-0.682	-5.36**	-1.15	-0.689	-3.94**	-0.39
Wholesale	-0.708	-4.73**	0.12	-0.784	-4.09**	-0.46
Retail	-0.816	-4.47**	0.10			
Restaurants, Hotel, Motel	-0.657	-5.14**	-0.63	1.241	-4.47**	-0.02
Insurance	-0.502	-4.78**	-0.10	-0.212	-4.48**	0.94
Trading				0.321	-4.45**	1.93
The rest	-0.567	-4.80**	-0.75	-0.672	-4.05**	-1.85

Table A.10. **VECM for selected average idiosyncratic risk**

This table reports VECM estimates for selected average idiosyncratic risk. The numbers in brackets are standard errors (first line) and bootstrapped standard errors (second line).

Dependent variables	Δ LIRs	$\Delta\ \gamma_t$
Constant	$5.12 * 10^{-5}$	-0.001
	(0.009)	(0.004)
	(0.009)	(0.004)
ECT	0.302	0.002
	(0.027**)	(0.012)
	(0.048**)	(0.009)
Lag1 Δ LIRs	-0.463	0.0004
	(0.040**)	(0.018)
	(0.063**)	(0.015)
Lag2 Δ LIRs	-0.218	-0.003
	(0.040**)	(0.018)
	(0.073**)	(0.012)
Lag1 $\Delta\ \gamma_t$	0.011	-0.282
	(0.982)	(0.045**)
	(0.092)	(0.164)
Lag2 $\Delta\ \gamma_t$	0.063	-0.131
	(0.983)	(0.045**)
	(0.083)	(0.076)

Table A.11. **The Market Model with GARCH(1,1) errors**

This table reports variance equation estimates for the Market Model with GARCH (1.1) errors. p-values are given in parentheses.

Company	ω_1	φ_1	φ_2	φ_3
Alcoa INC.	$2.82 * 10^{-5}$	0.156	0.604	$-8.36 * 10^{-6}$
	(0.0372)	(<0.0001)	(<0.0001)	(0.0058)
Amer. Intl. Group	$8.69 * 10^{-5}$	0.159	0.788	$1.34 * 10^{-5}$
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Amer. Express INC.	$4.62 * 10^{-5}$	0.203	0.653	$-1.87 * 10^{-6}$
	(<0.0001)	(0.0003)	(<0.0001)	(0.4209)
Boeing CO.	$1.65 * 10^{-4}$	0.168	0.616	$1.98 * 10^{-5}$
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Citigroup INC.	$-3.99 * 10^{-5}$	0.158	0.602	$-1.2 * 10^{-5}$
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Caterpillar INC.	$3.35 * 10^{-5}$	0.152	0.601	$-6.63 * 10^{-6}$
	(<0.0001)	(<0.0001)	(<0.0001)	(0.0659)
DuPont	$-3.83 * 10^{-5}$	0.163	0.607	$-1.69 * 10^{-5}$
	(0.0039)	(<0.0001)	(<0.0001)	(<0.0001)
Walt Disney CO.	$1.11 * 10^{-4}$	0.156	0.604	$1.21 * 10^{-5}$
	(<0.0001)	(<0.0001)	(<0.0001)	(0.0011)

Table A.11. **Continued**

Company	ω_1	ψ_1	ψ_2	ψ_3
Gen. Electric CO.	$2.13 * 10^{-5}$ (<0.0025)	0.154 (<0.0001)	0.602 (<0.0001)	$-3.36 * 10^{-6}$ (0.0132)
Gen. Motors	$-7.02 * 10^{-5}$ (<0.0001)	0.185 (<0.0001)	0.622 (<0.0001)	$-2.3 * 10^{-5}$ (<0.0001)
Home Depot INC.	$-6.02 * 10^{-5}$ (<0.0001)	0.181 (<0.0001)	0.693 (<0.0001)	$-1.6 * 10^{-5}$ (<0.0001)
Honeywell INTL. CO.	$2.14 * 10^{-6}$ (0.8255)	0.201 (<0.0001)	0.704 (<0.0001)	$-6.82 * 10^{-6}$ (0.0016)
Hewlett Packard CO.	$-2.09 * 10^{-4}$ (<0.0001)	0.162 (<0.0001)	0.600 (<0.0001)	$-6.12 * 10^{-5}$ (<0.0001)
Intl. Business Mach.	$-3.04 * 10^{-5}$ (0.0052)	0.171 (<0.0001)	0.612 (<0.0001)	$-1.16 * 10^{-5}$ (<0.0001)
Intel CP.	$-3.58 * 10^{-5}$ (0.1601)	0.170 (<0.0001)	0.615 (<0.0001)	$-3.06 * 10^{-5}$ (<0.0001)
Johnson and Johns. DC.	$-6.61 * 10^{-6}$ (0.4713)	0.203 (<0.0001)	0.636 (<0.0001)	$-8.97 * 10^{-6}$ (<0.0001)
JPMorgan Chase CO.	$1.45 * 10^{-4}$ (<0.0001)	0.191 (<0.0001)	0.634 (<0.0001)	$1.94 * 10^{-5}$ (<0.0001)
Coca Cola CO.	$1.96 * 10^{-5}$ (0.0357)	0.165 (<0.0001)	0.608 (<0.0001)	$-5.65 * 10^{-6}$ (0.0024)
McDonalds CP.	$2.05 * 10^{-4}$ (<0.0001)	0.180 (<0.0001)	0.624 (<0.0001)	$2.64 * 10^{-5}$ (<0.0001)
3M CO.	$-9.43 * 10^{-6}$ (0.3316)	0.193 (<0.0001)	0.629 (<0.0001)	$-9.27 * 10^{-6}$ (<0.0001)
Altria Group INC.	$6.69 * 10^{-5}$ (0.0013)	0.153 (<0.0001)	0.601 (<0.0001)	$1.24 * 10^{-8}$ (0.9975)
Merck CO. INC.	$2.27 * 10^{-5}$ (0.0683)	0.168 (<0.0001)	0.611 (<0.0001)	$-5.17 * 10^{-6}$ (0.0322)
Microsoft CP.	$-4.49 * 10^{-5}$ (<0.0001)	0.153 (<0.0001)	0.602 (<0.0001)	$-1.36 * 10^{-5}$ (<0.0001)
Pfizer INC.	$1.76 * 10^{-5}$ (0.0124)	0.132 (<0.0001)	0.797 (<0.0001)	$-8.95 * 10^{-7}$ (0.5132)
Procter and Gamble CO.	$-1.69 * 10^{-4}$ (<0.0001)	0.150 (0.0004)	0.601 (<0.0001)	$-4.7 * 10^{-5}$ (<0.0001)
ATT INC.	$-7.7 * 10^{-5}$ (<0.0001)	0.165 (<0.0001)	0.608 (<0.0001)	$-2.38 * 10^{-5}$ (<0.0001)
United Tech.	$1.02 * 10^{-4}$ (<0.0001)	0.157 (<0.0001)	0.605 (<0.0001)	$8.65 * 10^{-6}$ (0.0033)
Verizon Commun.	$-8.31 * 10^{-5}$ (0.5286)	0.156 (0.3034)	0.603 (0.1750)	$-2.22 * 10^{-5}$ (0.5150)
WalMart Stores	$1.3 * 10^{-4}$ (<0.0001)	0.192 (<0.0001)	0.636 (<0.0001)	$1.26 * 10^{-5}$ (<0.0001)
Exxon Mobil CP.	$-1.75 * 10^{-6}$ (0.0061)	0.189 (<0.0001)	0.625 (<0.0001)	$-9.71 * 10^{-6}$ (<0.0001)

Figure A.1. : **Idiosyncratic volatility**

This figure plots average idiosyncratic volatility (in logarithms) on U.S. market from 1963 till 2004.

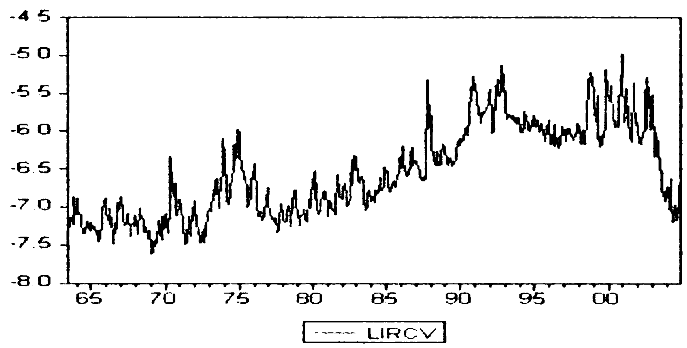


Figure A.2. : **Quasi-Herfindahl Index**

This figure plots average Quasi-Herfindahl Index (in logarithms) for U.S. market from 1963 till 2004.

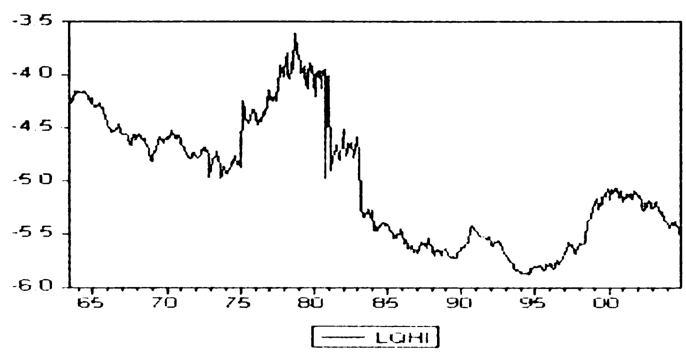


Figure A.3. : **Idiosyncratic fundamental volatility**

This figure plots three measures of average idiosyncratic fundamental volatility (in logarithms) on U.S. market for period 1963 - 2004. LICF, LIE, and LIS are the fundamental volatilities measured using cash flow, earnings, and sales, respectively.

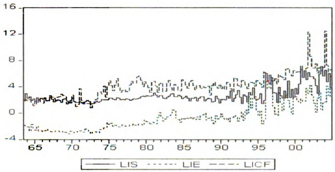
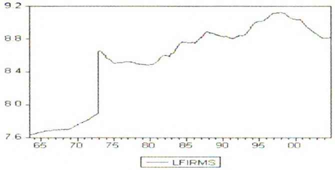


Figure A.4. : **Total number of securities**

This figure plots the total number of securities (in logarithms) on U.S. market from 1963 till 2004.



APPENDIX B

Tables and Figures for Essay 2

Table B.1. **Trends in idiosyncratic volatility of individual securities**

This table reports appearance of trends in securities' idiosyncratic volatility. The numbers represent the total number of securities in each category. Shares (in percentages) are given in parenthesis. The securities included in the samples are those with at least 2 years of monthly data. The columns refer to the sample of securities with significant (at least at 5% level) positive, significant negative, insignificant estimated trend coefficient, and the total sample. Idiosyncratic risk is measured as an average squared residual in monthly regressions of the Fama French three factor model.

Time period	Positive significant	Negative significant	Insignificant	Total
Jul 63 - Dec 05	6759	5548	9553	21860
Total period	(30.92%)	(25.38%)	(43.70%)	(100%)
Jul 63 - Dec 97	5410	3719	8220	17379
CLMX period	(31.30%)	(21.40%)	(47.30%)	(100%)
Jan 98 - Dec 05	1193	4521	4055	9769
Post CLMX period	(12.21%)	(46.28%)	(41.51%)	(100%)
Jul 63 - Dec 75	2258	363	3126	5747
	(39.29%)	(6.32%)	(54.39%)	(100%)
Jan 76 - Dec 85	1677	1554	4596	7827
	(21.43%)	(19.85%)	(58.72%)	(100%)
Jan 86 - Dec 95	3341	1988	5433	10762
	(31.04%)	(18.47%)	(50.49%)	(100%)
Jan 96 - Dec 05	2384	3861	5455	11700
	(20.38%)	(33.00%)	(46.62%)	(100%)

Table B.2. **Descriptive statistics of firm characteristics**

This table reports major statistical indicators for firm characteristics. All characteristics except turnover and size are in millions of dollars. Size is the logarithm of the market value of total equity, book-to-market is the ratio of book value to market value of equity, cash ratio is the ratio of cash to total assets, earnings per share is the ratio of earnings to the number of shares outstanding, leverage book value of long term debt to market value of assets, turnover is the share of the company's listed securities traded on the market per year, RnD expenditures is the ratio of RnD expenditures to market value of equity. N is the total number of non missing observations.

Characteristics	mean	standard deviation	minimum	maximum	skewness
size	4.29	2.21	-9.73	13.34	0.14
book-to-market	0.90	1.43	0	99.77	24.45
cash ratio	0.30	0.68	0	4.98	4.98
earnings per share	-1.29	1.37	-2.44	2.62	0.51
leverage	0.23	0.24	0	1	0.98
turnover	0.07	0.19	0.003	1.61	4.75
RnD expenditures	0.02	0.04	0	0.28	3.74

Table B.3. **Trend in idiosyncratic risk versus trend in firm characteristics**

The table describes a combined sample of estimated trends in firm characteristics and idiosyncratic risk (t^{ir}). t^{eps} is trend in earnings per share, t^{veps} is trend in volatility of earnings per share, t^{bm} is trend in book to market ratio, t^{turn} is trend in turnover, t^{cashr} is trend in cash ratio, t^{inst} is trend in institutional ownership share, t^{ret} is trend in excess returns, t^{p} is trend in the price (adjusted for inflation), t^{lev} is trend in leverage ratio, t^{rnd} is trend in research and development expenses and t^{size} is the trend in size. (+), (-), and (0) stand for positive significant, negative significant and insignificant trend subsample, respectively. The numbers represent the total number of securities in each category. Shares (in percentages) are given in parenthesis. Corr is the correlation coefficient of the trend dummies for idiosyncratic risk and each of the characteristics. N is the total number of securities available with measured trends for each of the firm characteristic. The securities are included if they have monthly volatility observations for at least two consecutive years.

Trend		t^{eps}			t^{veps}			t^{bm}			t^{turn}		
		(+)	(-)	(0)	(+)	(-)	(0)	(+)	(-)	(0)	(+)	(-)	(0)
	(+)	1781 (10.37%)	1298 (7.56%)	2040 (11.88%)	1560 (9.09%)	1570 (9.15%)	1989 (11.58%)	1117 (14.18%)	670 (8.50%)	785 (9.96%)	2453 (14.28%)	879 (5.12%)	1789 (10.41%)
t^{ir}	(-)	2827 (16.46%)	355 (2.07%)	1613 (9.39%)	957 (5.57%)	1619 (9.43%)	2219 (12.92%)	652 (8.26%)	888 (11.28%)	720 (9.14%)	3607 (21.00%)	279 (1.62%)	908 (5.29%)
	(0)	2914 (16.97%)	1266 (7.37%)	3077 (17.92%)	1989 (11.58%)	2200 (12.81%)	3070 (17.88%)	1106 (14.04%)	886 (11.25%)	1055 (13.39%)	3736 (21.75%)	967 (5.63%)	2555 (14.88%)
	Total	7522 (43.80%)	2919 (17.00%)	6730 (39.20)%)	4506 (26.24%)	5389 (31.39%)	7278 (42.38)%)	2875 (36.48%)	2444 (31.03%)	2560 (32.49)%)	9796 (57.03%)	2125 (12.37%)	5252 (30.58)%)
corr			0.000			0.026			0.054			0.004	
N			17173			17173			7879			17173	

Table B.3. **Continued**

Trend		t^{cashr}			t^{inst}			t^{ret}			t^{p}		
		(+)	(-)	(0)	(+)	(-)	(0)	(+)	(-)	(0)	(+)	(-)	(0)
	(+)	1143 (12.27%)	841 (9.02%)	1065 (11.43%)	976 (14.20%)	545 (7.93%)	512 (7.45%)	1480 (8.62%)	2037 (11.86%)	1604 (9.34%)	326 (1.90%)	4350 (25.33%)	445 (2.59%)
t^{ir}	(-)	671 (7.20%)	1056 (11.33%)	1012 (10.86%)	2020 (29.39%)	145 (2.11%)	280 (4.07%)	2014 (11.73%)	1177 (6.85%)	1602 (9.33%)	1848 (10.76%)	2176 (12.67%)	771 (4.49%)
	(0)	1047 (11.24%)	1119 (12.01%)	1365 (14.65%)	1625 (23.64%)	332 (4.83%)	438 (6.37%)	3167 (18.44%)	1779 (10.36%)	2313 (13.47%)	1645 (9.58%)	4480 (26.09%)	1132 (6.59%)
	Total	2861 (30.71%)	3016 (32.36%)	3442 (36.94)%	4621 (67.23%)	1022 (14.87%)	1230 (17.89)%	6661 (38.79%)	4993 (29.07%)	5519 (32.14)%	3819 (22.24%)	11006 (64.09%)	2348 (13.67)%
corr			0.057			-0.127			-0.069			-0.053	
N			9319			6873			17173			17173	

Table B.3. **Continued**

Trend		t^{lev}			t^{rnd}			t^{size}		
		(+)	(-)	(0)	(+)	(-)	(0)	(+)	(-)	(0)
t^{ir}	(+)	1528 (15.89%)	718 (7.47%)	905 (9.41%)	246 (8.89%)	142 (5.13%)	426 (15.40%)	1253 (11.85%)	1482 (14.02%)	610 (5.77%)
	(-)	978 (10.17%)	934 (9.71%)	859 (8.93%)	132 (4.77%)	207 (7.48%)	491 (17.75%)	2509 (23.73%)	256 (2.42%)	471 (4.46%)
	(0)	1512 (15.72%)	999 (10.39%)	1183 (12.30%)	274 (9.91%)	224 (8.10%)	624 (22.56%)	2253 (21.31%)	831 (7.86%)	907 (8.58%)
	Total	4018 (41.78%)	2651 (27.57%)	2947 (30.64)%)	652 (23.57%)	573 (20.71%)	1541 (55.71)%)	6015 (56.89%)	2569 (24.30%)	1988 (18.81)%)
corr			0.052			0.037			-0.067	
N			9616			2766			10572	

Table B.4. **Multinomial logit regressions**

This table describes results of multinomial logit regressions for firm characteristics. The dependent variable takes the value 1 if the security had a significant (at least at 5 %) positive trend, 2 - if significant negative, and 3 - if insignificant trend in idiosyncratic risk. The base case is insignificant trend, with probability Pr(0). Pr(+) and Pr(-) are the probabilities of having a significant positive and a significant negative trend in idiosyncratic volatility, respectively. Regressors are dummy variables for trends in each of the firm characteristics. Positive sign indicate that the dummy takes the value 1 in case of the positive significant trend and 0 otherwise, negative sign indicates that the dummy takes the value 1 in case of the negative significant trend and 0 otherwise. Standard errors are given in parenthesis. Bold fase characters indicate significance at least at 1 % level.

Regressors	$log(\frac{Pr(+)}{Pr(0)})$					$log(\frac{Pr(-)}{Pr(0)})$				
intercept	**-1.186**	**-1.188**	**-1.184**	**-1.197**	**-0.741**	**-0.861**	**-0.861**	**-0.855**	**-0.615**	**-0.912**
	(0.075)	**(0.075)**	**(0.074)**	**(0.073)**	**(0.050)**	**(0.069)**	**(0.069)**	**(0.068)**	**(0.065)**	**(0.052)**
eps^+	**-0.295**	**-0.298**	**-0.263**	**-0.308**	**-0.369**	**0.210**	**0.197**	**0.184**	**0.567**	**0.296**
	(0.055)	**(0.055)**	**(0.054)**	**(0.048)**	**(0.054)**	**(0.055)**	**(0.055)**	**(0.055)**	**(0.048)**	**(0.054)**
eps^-	**0.362**	**0.362**	**0.359**	**0.358**	**0.433**	**-0.451**	**-0.445**	**-0.456**	**-0.622**	**-0.514**
	(0.062)	**(0.062)**	**(0.062)**	**(0.055)**	**(0.061)**	**(0.077)**	**(0.077)**	**(0.077)**	**(0.071)**	**(0.076)**
$veps^+$	**0.409**	**0.413**	**0.411**	**0.405**	**0.349**	**-0.683**	**-0.675**	**-0.712**	**-0.593**	**-0.614**
	(0.051)	**(0.050)**	**(0.050)**	**(0.050)**	**(0.049)**	**(0.055)**	**(0.054)**	**(0.054)**	**(0.054)**	**(0.053)**
$veps^-$	-0.007	-0.007	-0.017	-0.002	-0.004	0.000	-0.008	0.000	-0.052	-0.020
	(0.051)	(0.051)	(0.050)	(0.050)	(0.050)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)
bm^+	-0.048	-0.059	-0.073	-0.056	-0.027	**-0.221**	**-0.243**	**-0.199**	**-0.242**	**-0.289**
	(0.063)	(0.062)	(0.062)	(0.062)	(0.062)	**(0.069)**	**(0.068)**	**(0.067)**	**(0.068)**	**(0.068)**
bm^-	0.139	0.140	0.134	0.136	**0.191**	-0.019	-0.042	-0.017	0.012	-0.065
	(0.073)	(0.073)	(0.072)	(0.072)	**(0.072)**	(0.068)	(0.068)	(0.066)	(0.067)	(0.066)
$cashr^+$	**0.201**	**0.188**	**0.188**	**0.186**	**0.210**	**-0.192**	**-0.220**	**-0.172**	**-0.188**	**-0.239**
	(0.063)	**(0.062)**	**(0.062)**	**(0.062)**	**(0.062)**	**(0.069)**	**(0.069)**	**(0.068)**	**(0.068)**	**(0.068)**
$cashr^-$	**0.196**	**0.197**	**0.190**	**0.199**	**0.217**	-0.148	-0.146	-0.091	-0.157	-0.155
	(0.067)	**(0.067)**	**(0.066)**	**(0.067)**	**(0.066)**	(0.064)	(0.064)	(0.062)	(0.063)	(0.062)
ins^+	**-0.216**	**-0.223**		**-0.238**	**-0.159**	**0.556**	**0.536**		**0.635**	**0.499**
	(0.057)	**(0.057)**		**(0.055)**	**(0.056)**	**(0.054)**	**(0.054)**		**(0.054)**	**(0.053)**
ins^-	**0.449**	**0.444**		**0.439**	**0.514**	-0.114	-0.130		-0.131	-0.209
	(0.082)	**(0.082)**		**(0.082)**	**(0.082)**	(0.114)	(0.114)		(0.112)	(0.112)
lev^+	**0.229**	**0.229**	**0.224**	**0.227**	**0.253**	**-0.376**	**-0.369**	**-0.348**	**-0.345**	**-0.396**
	(0.056)	**(0.056)**	**(0.056)**	**(0.056)**	**(0.056)**	**(0.060)**	**(0.060)**	**(0.059)**	**(0.059)**	**(0.059)**
lev^-	0.090	0.090	0.089	0.089	0.112	-0.162	**-0.175**	-0.143	-0.161	**-0.187**
	(0.070)	(0.070)	(0.069)	(0.070)	(0.069)	(0.067)	**(0.066)**	(0.065)	(0.066)	**(0.065)**
$size^+$	0.033	0.038	-0.025	0.024	-0.129	**0.410**	**0.404**	**0.609**	**0.483**	**0.532**
	(0.062)	(0.062)	(0.059)	(0.061)	(0.061)	**(0.059)**	**(0.059)**	**(0.055)**	**(0.059)**	**(0.057)**
$size^-$	**0.805**	**0.797**	**0.863**	**0.792**	**0.961**	**-0.258**	**-0.269**	**-0.264**	**-0.253**	**-0.420**
	(0.061)	**(0.061)**	**(0.060)**	**(0.061)**	**(0.061)**	**(0.085)**	**(0.085)**	**(0.086)**	**(0.086)**	**(0.083)**
$turn^+$	-0.040	-0.043	-0.084		0.008	**0.794**	**0.787**	**0.865**		**0.719**
	(0.052)	(0.052)	(0.051)		(0.051)	**(0.060)**	**(0.060)**	**(0.060)**		**(0.059)**
$turn^-$	-0.020	-0.018	-0.017		-0.050	-0.067	-0.065	-0.054		-0.024
	(0.069)	(0.069)	(0.069)		(0.068)	(0.088)	(0.088)	(0.087)		(0.087)
ret^+	**-0.357**	**-0.354**	**-0.344**	**-0.355**	**-0.394**	-0.070	-0.064	-0.086	-0.063	-0.012
	(0.048)	**(0.048)**	**(0.048)**	**(0.048)**	**(0.047)**	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)
ret^-	**0.487**	**0.485**	**0.486**	**0.486**	**0.512**	0.044	0.041	0.041	0.016	0.018
	(0.048)	**(0.048)**	**(0.048)**	**(0.048)**	**(0.048)**	(0.053)	(0.053)	(0.052)	(0.052)	(0.052)
p^+	**-0.578**	**-0.575**	**-0.574**	**-0.574**		**0.439**	**0.441**	**0.439**	**0.413**	
	(0.084)	**(0.084)**	**(0.084)**	**(0.084)**		**(0.061)**	**(0.061)**	**(0.061)**	**(0.061)**	
p^-	**0.720**	**0.722**	**0.720**	**0.721**		**-0.286**	**-0.284**	**-0.268**	**-0.258**	
	(0.062)	**(0.062)**	**(0.062)**	**(0.062)**		**(0.057)**	**(0.057)**	**(0.056)**	**(0.056)**	
rnd^+	-0.217					**-0.373**				
	(0.102)					**(0.120)**				
rnd^-	0.042					**-0.435**				
	(0.120)					**(0.111)**				

Table B.5. **Sub-sample multinomial logit regressions**

This table describes results of multinomial logit regressions for firm characteristics for sub-samples. The original sample is split by price (low-high), time period (CLMX and post-CLMX), security life (long-short), and date security was listed (early-late). The dependent variable takes the value 1 if the security had a significant (at least at 5 %) positive trend, 2 - if significant negative, and 3 - if insignificant trend in idiosyncratic risk. The base case is insignificant trend, with probability Pr(0). Pr(+) and Pr(-) are the probabilities of having a significant positive and a significant negative trend in idiosyncratic volatility, respectively. Regressors are dummy variables for trends in each of the firm characteristics. Positive sign indicate that the dummy takes the value 1 in case of the positive significant trend and 0 otherwise, negative sign indicates that the dummy takes the value 1 in case of the negative significant trend and 0 otherwise. Standard errors are given in parenthesis. Bold fase characters indicate significance at least at 1 % level.

Regressors	$log(\frac{Pr(+)}{Pr(0)})$				$log(\frac{Pr(-)}{Pr(0)})$			
	p^{high}	p^{low}	CLMX	post-CLMX	p^{high}	p^{low}	CLMX	post-CLMX
intercept	**-1.401**	**-0.962**	**-1.095**	**-1.385**	**-0.595**	**-1.639**	**-1.353**	**0.252**
	(0.095)	**(0.129)**	**(0.061)**	**(0.138)**	**(0.077)**	**(0.159)**	**(0.063)**	**(0.080)**
eps^+	**-0.195**	**-0.514**	0.117	-0.015	**0.185**	**0.771**	**-0.407**	**0.337**
	(0.069)	**(0.095)**	(0.073)	(0.258)	**(0.061)**	**(0.142)**	**(0.084)**	**(0.115)**
eps^-	**0.346**	**0.488**	0.159	**0.580**	**-0.439**	**-0.798**	**-0.638**	**0.542**
	(0.077)	**(0.110)**	(0.085)	**(0.119)**	**(0.083)**	**(0.221)**	**(0.110)**	**(0.075)**
$ceps^+$	**0.492**	**0.309**	**-0.314**	0.092	**-0.718**	**-0.503**	**-0.440**	**0.183**
	(0.064)	**(0.084)**	**(0.061)**	(0.108)	**(0.061)**	**(0.128)**	**(0.067)**	**(0.069)**
$ceps^-$	-0.048	0.025	0.029	**-0.528**	-0.053	0.257	0.032	**-0.421**
	(0.066)	(0.078)	(0.063)	**(0.114)**	(0.057)	(0.103)	(0.070)	**(0.074)**
bm^+	-0.192	0.106	-0.076	**-0.251**	**-0.246**	-0.103	-0.153	**-0.261**
	(0.081)	(0.098)	(0.055)	**(0.096)**	**(0.079)**	(0.147)	(0.067)	**(0.066)**
bm^-	0.044	**0.351**	0.012	0.087	-0.036	-0.094	**0.197**	-0.040
	(0.086)	**(0.137)**	(0.060)	(0.132)	(0.074)	(0.165)	**(0.058)**	(0.071)
$cashr^+$	**0.258**	0.085	0.069	-0.242	-0.146	-0.322	-0.040	**-0.317**
	(0.080)	(0.102)	(0.058)	(0.100)	(0.079)	(0.152)	(0.071)	**(0.066)**
$cashr^-$	**0.239**	0.100	-0.045	-0.049	-0.111	-0.118	-0.012	0.045
	(0.082)	(0.115)	(0.056)	(0.130)	(0.071)	(0.145)	(0.058)	(0.071)
ins^+	-0.117	**-0.369**	**-0.160**	**-1.800**	**0.422**	**0.502**	**0.302**	**-0.988**
	(0.066)	**(0.123)**	**(0.050)**	**(0.099)**	**(0.060)**	**(0.137)**	**(0.053)**	**(0.060)**
ins^-	**0.535**	**0.354**	0.087	**0.301**	-0.003	-0.351	0.093	0.053
	(0.117)	**(0.116)**	(0.062)	**(0.101)**	(0.140)	(0.219)	(0.082)	(0.081)
lev^+	**0.184**	**0.313**	**0.167**	-0.052	**-0.377**	**-0.453**	-0.050	-0.005
	(0.071)	**(0.093)**	**(0.054)**	(0.094)	**(0.067)**	**(0.135)**	(0.061)	(0.064)
lev^-	0.115	0.038	0.067	**-0.533**	-0.122	**-0.394**	0.016	-0.105
	(0.087)	(0.117)	(0.062)	**(0.116)**	(0.075)	**(0.151)**	(0.062)	(0.067)
$size^+$	0.064	0.157	**-0.241**	**-1.183**	**0.378**	0.125	**0.695**	**-0.871**
	(0.073)	(0.129)	**(0.061)**	**(0.138)**	**(0.066)**	(0.140)	**(0.071)**	**(0.071)**
$size^-$	**0.942**	**0.698**	**0.375**	**0.803**	0.011	**-0.502**	**-0.473**	**0.551**
	(0.085)	**(0.094)**	**(0.059)**	**(0.097)**	(0.106)	**(0.151)**	**(0.097)**	**(0.075)**
$turn^+$	-0.006	0.013	**0.213**	-0.412	**0.683**	**0.646**	**0.578**	**0.208**
	(0.066)	(0.091)	**(0.059)**	(0.164)	**(0.066)**	**(0.145)**	**(0.081)**	**(0.074)**
$turn^-$	0.118	-0.256	-0.023	**0.697**	-0.064	0.221	0.299	**0.448**
	(0.092)	(0.111)	(0.104)	**(0.088)**	(0.099)	(0.210)	(0.142)	**(0.059)**
ret^+	**-0.335**	**-0.338**	**-0.275**	-0.064	**-0.192**	**0.306**	0.009	**0.472**
	(0.062)	**(0.077)**	**(0.097)**	(0.277)	**(0.053)**	**(0.100)**	(0.089)	**(0.138)**
ret^-	**0.462**	**0.511**	**1.308**	**2.229**	0.041	-0.073	-0.018	0.277
	(0.064)	**(0.076)**	**(0.100)**	**(0.212)**	(0.060)	(0.123)	(0.172)	(0.218)
p^+	**-0.617**	**-0.460**	**-0.353**	**-0.955**	**0.390**	**0.724**	**0.448**	-0.067
	(0.101)	**(0.161)**	**(0.074)**	**(0.193)**	**(0.067)**	**(0.147)**	**(0.064)**	(0.073)
p^-	**0.782**	**0.626**	**0.827**	**0.664**	**-0.203**	**-0.394**	0.059	-0.036
	(0.077)	**(0.112)**	**(0.059)**	**(0.119)**	**(0.064)**	**(0.126)**	(0.062)	(0.070)

Table B.5. **Continued**

Regressors	$log(\frac{Pr(+)}{Pr(0)})$				$log(\frac{Pr(-)}{Pr(0)})$			
	$life^{short}$	$life^{long}$	$listed^{early}$	$listed^{late}$	$life^{short}$	$life^{long}$	$listed^{early}$	$listed^{late}$
intercept	**-1.262**	**-0.891**	**-1.110**	**-1.400**	**-1.349**	-0.225	**-1.253**	-0.160
	(0.100)	**(0.120)**	**(0.087)**	**(0.156)**	**(0.100)**	(0.112)	**(0.093)**	(0.115)
eps^+	**-0.369**	**-0.312**	**-0.247**	**-0.344**	**0.700**	**-0.190**	-0.090	**0.308**
	(0.086)	**(0.074)**	**(0.071)**	**(0.093)**	**(0.089)**	**(0.072)**	(0.079)	**(0.083)**
eps^-	**0.346**	**0.324**	**0.442**	**0.255**	**-0.942**	**-0.436**	**-0.580**	**-0.366**
	(0.100)	**(0.085)**	**(0.086)**	**(0.097)**	**(0.144)**	**(0.095)**	**(0.112)**	**(0.110)**
$veps^+$	**0.372**	**0.557**	**0.469**	**0.287**	**-1.167**	**-0.373**	**-0.738**	**-0.673**
	(0.075)	**(0.071)**	**(0.064)**	**(0.085)**	**(0.090)**	**(0.074)**	**(0.079)**	**(0.081)**
$veps^-$	-0.058	0.054	-0.039	0.039	**0.340**	**-0.263**	-0.101	0.118
	(0.077)	(0.069)	(0.062)	(0.090)	**(0.080)**	**(0.066)**	(0.068)	(0.077)
bm^+	-0.132	-0.023	-0.028	-0.052	-0.079	**-0.255**	-0.198	0.013
	(0.118)	(0.074)	(0.073)	(0.127)	(0.150)	**(0.077)**	(0.084)	(0.127)
bm^-	0.223	0.090	**0.260**	-0.052	0.037	-0.019	**-0.390**	0.196
	(0.198)	(0.079)	**(0.102)**	(0.108)	(0.186)	(0.071)	**(0.097)**	(0.100)
$cashr^+$	0.242	0.154	0.050	**0.487**	0.148	**-0.272**	**-0.303**	0.201
	(0.122)	(0.074)	(0.076)	**(0.114)**	(0.149)	**(0.077)**	**(0.088)**	(0.118)
$cashr^-$	-0.210	**0.256**	0.150	0.201	-0.372	-0.061	-0.102	-0.125
	(0.152)	**(0.075)**	(0.086)	(0.104)	(0.150)	(0.069)	(0.083)	(0.101)
ins^+	-0.219	**-0.259**	**-0.509**	**0.288**	**0.939**	**0.481**	**0.793**	**0.485**
	(0.141)	**(0.064)**	**(0.072)**	**(0.095)**	**(0.120)**	**(0.062)**	**(0.071)**	**(0.090)**
ins^-	**0.554**	**0.355**	**0.261**	**0.932**	-0.164	-0.152	0.079	0.109
	(0.153)	**(0.098)**	**(0.094)**	**(0.176)**	(0.230)	(0.130)	(0.139)	(0.216)
lev^+	0.143	**0.238**	**0.263**	0.202	**-0.517**	**-0.325**	**-0.232**	**-0.438**
	(0.111)	**(0.067)**	**(0.071)**	(0.095)	**(0.128)**	**(0.068)**	**(0.077)**	**(0.099)**
lev^-	0.038	0.069	0.131	0.045	**-0.530**	-0.060	-0.144	-0.208
	(0.157)	(0.079)	(0.094)	(0.109)	**(0.155)**	(0.072)	(0.090)	(0.101)
$size^+$	0.039	-0.079	-0.004	0.111	0.282	**0.478**	**0.720**	0.018
	(0.149)	(0.074)	(0.078)	(0.106)	(0.122)	**(0.075)**	**(0.080)**	(0.096)
$size^-$	**0.800**	**0.785**	**0.874**	**0.728**	**-0.539**	**-0.306**	0.073	**-0.575**
	(0.108)	**(0.081)**	**(0.075)**	**(0.109)**	**(0.142)**	**(0.113)**	(0.112)	**(0.136)**
$turn^+$	-0.114	-0.037	-0.092	0.043	**1.211**	**0.244**	**0.650**	**0.679**
	(0.080)	(0.074)	(0.068)	(0.084)	**(0.093)**	**(0.082)**	**(0.084)**	**(0.090)**
$turn^-$	0.022	-0.043	-0.122	0.166	-0.117	0.063	-0.109	**0.404**
	(0.100)	(0.106)	(0.087)	(0.143)	(0.136)	(0.125)	(0.112)	**(0.153)**
ret^+	**-0.490**	**-0.272**	**-0.271**	**-0.433**	0.142	**-0.287**	**-0.180**	-0.039
	(0.072)	**(0.066)**	**(0.061)**	**(0.080)**	(0.073)	**(0.063)**	**(0.066)**	(0.071)
ret^-	**0.629**	**0.330**	**0.572**	**0.252**	0.027	0.064	0.159	-0.143
	(0.068)	**(0.069)**	**(0.058)**	**(0.089)**	(0.083)	(0.072)	(0.069)	(0.086)
p^+	**-0.629**	**-0.532**	**-0.577**	**-0.550**	0.585	0.400	0.691	0.110
	(0.118)	**(0.123)**	**(0.096)**	**(0.183)**	(0.089)	(0.091)	(0.082)	(0.102)
p^-	**0.785**	**0.554**	**0.658**	**0.865**	**-0.400**	**-0.256**	**-0.284**	**-0.555**
	(0.085)	**(0.093)**	**(0.073)**	**(0.135)**	**(0.083)**	**(0.083)**	**(0.079)**	**(0.092)**

Table B.6. **Regressions on trend coefficients**

This table reports results of the regressions on estimated trend coefficients. The dependent variable is estimated value of the trend coefficient from first stage time-series regressions. All numbers are scaled by 10^4. Model (1) includes the total sample and uses least squares regression. Model (2)((3)) includes only firms with positive (negative) significant (at 5 %) estimates of trend coefficient and uses Tobit regression. Standard errors are given in parenthesis. Bold fase characters indicate significance at 1 % level.

Regressors	(1)		(2)		(3)	
intercept	**0.181**	**0.177**	**0.417**	**0.398**	**-0.115**	**-0.093**
	(0.033)	**(0.013)**	**(0.079)**	**(0.034)**	**(0.019)**	**(0.011)**
eps	-0.847	**-1.677**	6.067	-1.924	-0.694	**-0.648**
	(0.922)	**(0.541)**	(5.866)	(1.923)	(0.480)	**(0.240)**
veps	**3.131**	**2.143**	0.287	-0.540	**1.383**	**1.132**
	(0.600)	**(0.478)**	(4.057)	(2.395)	**(0.414)**	**(0.294)**
bm	0.448	0.775	0.063	0.047	0.441	0.414
	(0.394)	(0.328)	(0.938)	(0.496)	(0.655)	(0.331)
cashr	-1.559	-0.380	-5.968	-2.408	3.214	0.618
	(2.689)	(1.068)	(5.577)	(2.251)	(1.637)	(1.267)
ins	**-7.082**	**-3.685**	-9.890	-6.609	-2.571	-1.008
	(1.287)	**(1.015)**	(5.883)	(3.431)	(1.105)	(0.697)
lev	3.582	4.572	4.887	6.658	2.083	-0.065
	(2.995)	(1.978)	(8.825)	(4.005)	(1.742)	(0.952)
size	**-2.858**	**-3.944**	**-6.330**	**-7.602**	**1.659**	**0.922**
	(0.726)	**(0.376)**	**(1.725)**	**(0.921)**	**(0.331)**	**(0.244)**
turn	-1.108	-1.692	-26.082	-10.720	**-5.064**	**-5.323**
	(2.197)	(1.715)	(22.849)	(8.639)	**(1.287)**	**(1.244)**
ret	89.901	3.796	235.431	64.751	10.205	29.374
	(119.067)	(74.649)	(222.294)	(107.976)	(31.032)	(49.320)
p	23.032	0.187	26.593	**52.929**	3.145	-7.457
	(10.887)	(0.097)	(14.102)	**(14.228)**	(9.082)	(5.650)
RnD	62.446		62.192		33.141	
	(32.121)		(46.157)		(22.693)	

Figure B.1. : **Market composition effect**

This figure plots market composition effect on average idiosyncratic risk. Irff is market average idiosyncratic risk computed using Fama and French monthly regressions, Irstr is market average idiosyncratic risk where risk of securities with a trend (positive or negative) is set equal to its starting value.

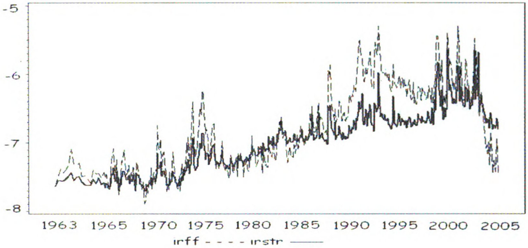


Figure B.2. : **Market average risk with positive trends removed.**

This figure plots market composition effect when positive firm-level trend is removed. Irff is market average idiosyncratic risk computed using Fama and French monthly regressions, Irnop is market average idiosyncratic risk where risk of securities with a positive trend is set equal to its starting value.

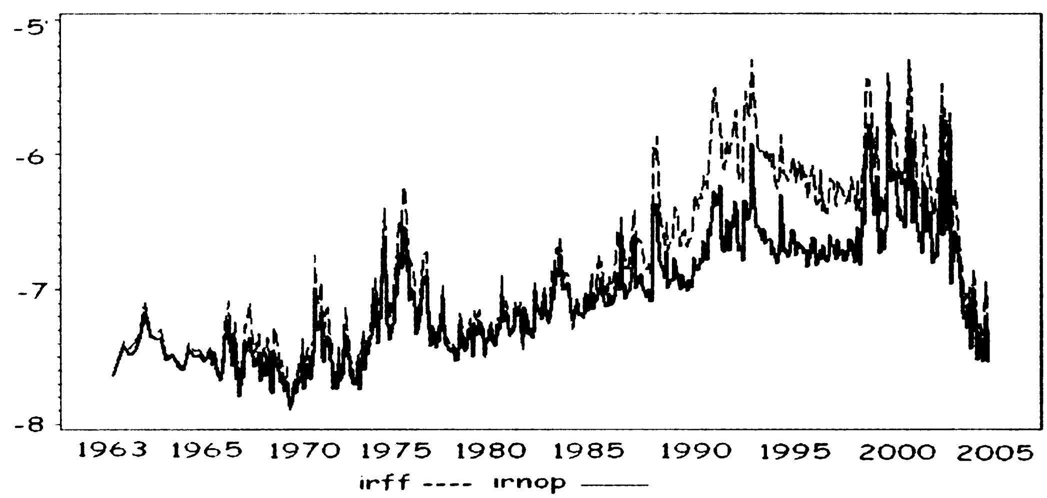


Figure B.3. : **Market average risk with negative trends removed.**

This figure plots market composition effect when negative firm-level trend is removed. Irff is market average idiosyncratic risk computed using Fama and French monthly regressions, Irnon is market average idiosyncratic risk where risk of securities with a negative trend is set equal to its starting value.

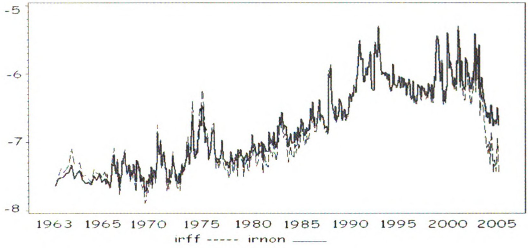


Figure B.4. : **Idiosyncratic volatility of the NASDAQ firms**

This figure plots idiosyncratic volatility of the NASDAQ sample of sequrities.

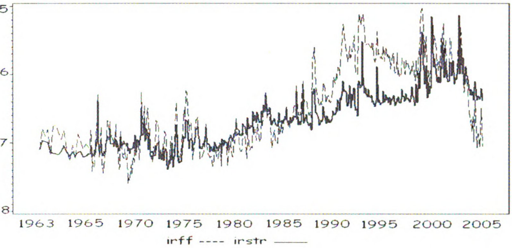


Figure B.5. : **Idiosyncratic volatility of the non-NASDAQ firms**

This figure plots idiosyncratic volatility of the non-NASDAQ sample of sequrities.

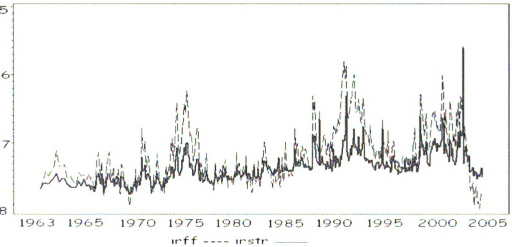


Figure B.6. : **Idiosyncratic volatility of the new firms**

This figure plots idiosyncratic volatility of the new firms in each month.

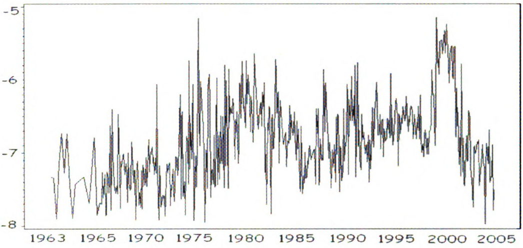


Figure B.7. : **Idiosyncratic volatility excluding new firms**

This figure plots idiosyncratic volatility excluding new firms in each month.

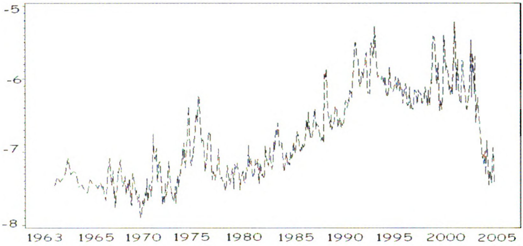


Figure B.8. : **Idiosyncratic volatility of the 1980 firms**

This figure plots idiosyncratic volatility of the firms first listed in January 1980.

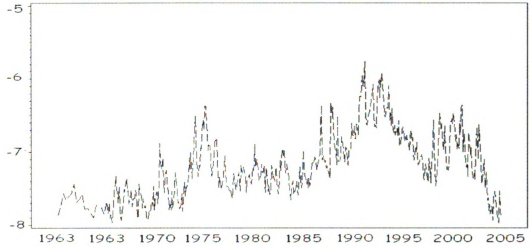
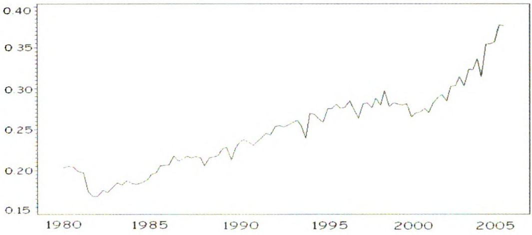


Figure B.9. : **Institutional ownership**

This figure plots average institutional ownership share.



APPENDIX C

Tables and Figures for Essay 3

Table C.1. **Augmented Dickey-Fuller unit root tests**

This table reports results of Augmented Dickey-Fuller tests for main variables. All tests include four lags, other specifications provide similar results and are available upon request. CV are MacKinnon critical values are equal -3.50 for the 1% level and -2.89 for the 5% level. The null hypothesis is the unit root in the data. The data range is 1980:1 - 2004:4.

Variables	ADF statistic
INS	-1.58
IRFF	-2.28

Table C.2. **Rolling cointegration and VEC model estimates**

This table reports estimated coefficients on error correction term (ECT) in VECM for the relationship between institutional ownership (INS) and idiosyncratic risk (IRFF) rolled by one year. The last column contains Likelihood Ratio statistics for Johansen cointegration tests, for which critical values are 20.04 (1%) and 15.41 (5%) (except for the last line, for which the values are 35.65 and 29.68, respectively). t statistics are given in parentheses.

ECT	Δ INS	Δ IRFF	LR
1980:1 - 1999:4	-0.142	0.009	19.19**
	(-2.57)	(2.47)	
1981:1 - 2000:4	-0.189	-0.010	17.31*
	(-2.25)	(-1.57)	
1982:1 - 2001:4	-0.007	0.001	15.55*
	(-1.40)	(3.20)	
1983:1 - 2002:4	-0.004	0.001	16.49*
	(-1.16)	(3.33)	
1984:1 - 2003:4	0.012	-0.002	13.92
	(1.07)	(-2.79)	
1985:1 - 2004:4	-0.086	-0.009	12.27
	(-1.56)	(-2.35)	

Table C.3. **VEC model for idiosyncratic risk and institutional ownership**

This table reports estimated VECM for the relationship between institutional ownership (INS) and idiosyncratic risk (IRFF) with a dummy variable included for observations 2000:2 - 2004:4. ECT is the error correction term. DV is the dependent variable. t statistics are given in parentheses. The data range is 1980:1 - 2004:4.

DV	Δ INS	Δ IRFF
Constant	0.000	-0.000
	(0.30)	(-0.34)
ECT	-0.016	0.001
	(-2.52)	(2.43)
Δ INS* lag1	-0.439	-0.000
	(-4.07)	(-0.04)
Δ INS* lag2	-0.065	-0.003
	(-0.61)	(-0.40)
ΔIRFF lag1	-2.491	-0.368
	(-1.56)	(-3.58)
ΔIRFF lag2	0.562	-0.365
	(0.36)	(-3.66)
R-squared	0.21	0.29

Figure C.1. : **Idiosyncratic risk adjustments to shock in VECM**

This figure plots changes of idiosyncratic volatility due to a single shock in the VECM of two variables (institutional ownership and idiosyncratic risk).

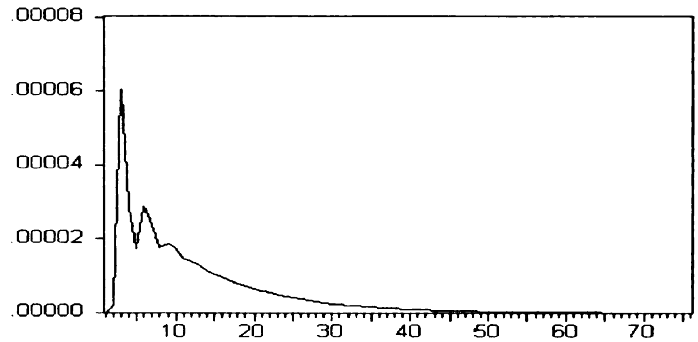


Figure C.2. : **Institutional ownership adjustments to shock in VECM**

This figure plots changes of institutional ownership due to a single shock in the VECM of two variables (institutional ownership and idiosyncratic risk).

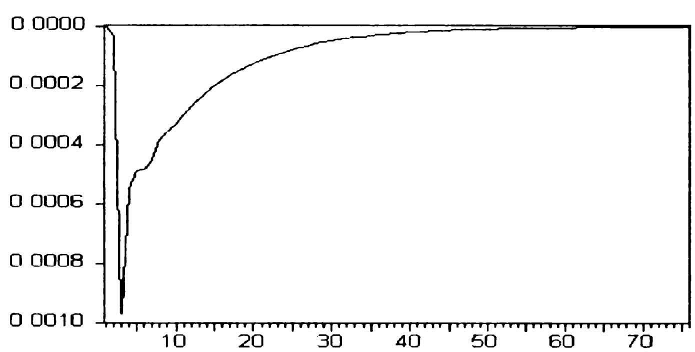


Figure C.3. : **Idiosyncratic volatility**

This figure plots average idiosyncratic volatility (detrended) on U.S. market from 1963 till 2005.

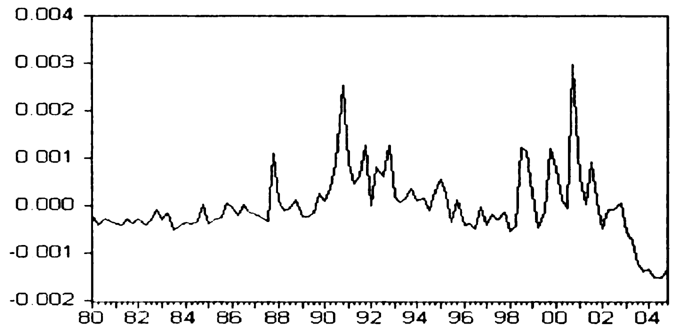
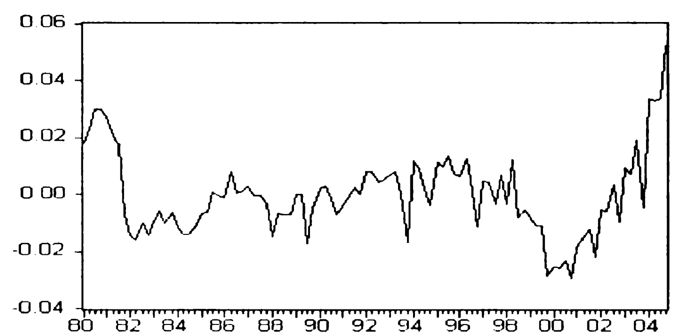


Figure C.4. : **Institutional ownership**

This figure plots average institutional ownership share (detrended) on U.S. market from 1963 till 2005.



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