Has Idiosyncratic Volatility Increased? Not in Recent Times

Mardy Chiah,[*] Philip Gharghori,[†] and Angel Zhong[‡]

September 2020

Forthcoming in *Critical Finance Review*

JEL Classification: G12

Keywords: idiosyncratic volatility, market volatility, asset pricing

Acknowledgements: We are grateful to an anonymous referee and the guest editor, Juhani Linnainmaa, for helpful comments.

---

* Department of Accounting, Economics and Finance, Swinburne Business School, Swinburne University of Technology, Melbourne Australia

† Monash Business School, Monash University, Melbourne Australia

‡ School of Economics, Finance and Marketing, RMIT University, Melbourne Australia

Has Idiosyncratic Volatility Increased? Not in Recent Times

Abstract

This study successfully replicates the key findings of Campbell, Lettau, Malkiel, and Xu (2001). We document that aggregate idiosyncratic volatility increases over their sample period from 1962 to 1997. In out-of-sample analysis from 1926 to 1962 and 1998 to 2017, we find that idiosyncratic volatility (IV) decreases, suggesting that their finding is sample-specific. We compare their measure of IV with those obtained from models such as the Fama and French (1993) three-factor model and find that they are very similar. The Campbell et al. (2001) volatility measures can only be estimated at the aggregate level. An advantage of asset pricing model-based IVs is that they can be estimated at the stock level. Employing these stock-level IV measures, we examine trends in a variety of IV series and how IV relates to commonly analyzed firm characteristics. In doing so, we provide further insight into IV and its time-series trends.

JEL Classification: G12

Keywords: idiosyncratic volatility, market volatility, asset pricing

1 Introduction

Disaggregating volatility into its market, industry, and firm components, Campbell, Lettau, Malkiel, and Xu (2001) (CLMX hereafter) investigate the trend in volatility at different levels in the U.S. equity market from July 1962 to December 1997. They find that firm-level (idiosyncratic) volatility follows an upward trend relative to market volatility. This finding is important for a number of reasons. First, under-diversified investors are acutely affected by changes in volatility at both the industry and firm levels. Second, an increase in idiosyncratic volatility indicates that a larger number of stocks are required for diversification in equity investment. Third, idiosyncratic volatility is a prominent source of arbitrage costs in the limits-to-arbitrage literature (Shleifer and Vishny, 1997), where investors become reluctant to correct mispricing when arbitrage costs exceed the benefits of doing so. This observed upward trend in aggregate idiosyncratic volatility has led to a voluminous amount of research investigating both trends in idiosyncratic volatility and its determinants.[1]

To revisit the main findings of CLMX, we start by repeating their analysis over the same period, 1962 to 1997, and strictly following their method and data selection criteria. Next, we conduct out-of-sample analysis. With the availability of daily data prior to 1962, we can repeat the analysis in both the pre-CLMX period (January 1926 to June 1962) and the post-CLMX period (1998 to 2017). With the recent advancements in asset pricing research, we also estimate idiosyncratic volatility (IV hereafter) using prevalent asset pricing models and explore trends in asset pricing model-based IV. Furthermore, we investigate the characteristics of stocks with different levels of IV. Finally, we look into the IV of characteristics-sorted groups for a complete picture of the relation between IV and firm characteristics.

[1] See, for example, Xu and Malkiel (2003), Bennet et al. (2003), Wei and Zhang (2006), Brown and Kapadia (2007), Cao et al. (2008), Irvine and Pontiff (2009), Fink et al. (2010), Brandt et al. (2010), Bekaert et al. (2012), and Kang et al. (2014).

Our major findings are summarized as follows. First, we successfully replicate CLMX's major findings over the same period, 1962 to 1997. Consistent with CLMX, aggregate IV increases using the FIRM measure of CLMX. Correspondingly, *R*-squares estimated from the market model decrease and the number of stocks required for diversification increases over the CLMX period. Our volatility series are very close to CLMX's, as evidenced by correlations of around 0.99 in comparison with their series, which are available from John Campbell's website. The volatility series also exhibit an ability to forecast future GDP growth.

Second, results are robust to IV measures computed using different asset pricing models. Using asset pricing models, we construct IV-MM, IV-FF3, IV-FF5, and IV-FF6 to represent IV estimated with the market model, the Fama and French (1993) three-factor model, and the Fama and French (2015) five- and six-factor (FF5 plus momentum factor) models, respectively. The FIRM measure in CLMX that captures aggregate firm-level volatility is only computed at the market level. A key advantage of IV estimated using asset pricing models is that it is available at the individual firm level.

Third, out-of-sample analysis suggests that CLMX's finding is likely to be sample specific. In both the pre- and post-CLMX periods, IV does not exhibit an increasing trend. On the contrary, it decreases. This finding is robust to different IV measures. It is also corroborated by an increase in market model *R*-squares and a decrease in the number of stocks required for a diversified portfolio in the post-CLMX period. Idiosyncratic volatility spikes during both the dot-com crash in 2000 and the 2008 financial crisis, but in the calm market periods before and after the financial crisis, it is at levels last seen in the 1960s. The decline in IV we document after the dot-com crash is consistent with a series of papers post-CLMX, the most recent Bartram et al. (2019).[2] An interesting counterpoint to the decline in aggregate IV over the past 20 years is that the cross-sectional variability in stock-level IV has increased markedly. This is evidenced by increases in cross-sectional standard deviation,

[2] Brandt et al. (2010) and Bekaert et al. (2012) are two other recent examples.

skewness, and kurtosis. One area in which the findings in the post-CLMX period mirror the original study is that the volatility series continue to exhibit forecasting power on future GDP growth.

Fourth, we analyze time-series trends in IV in stocks sorted into IV quintile groups. We observe that the spread in IV between the low- and high-IV groups has been widening from the 1950s until the dot-com crash. It has since narrowed to a level last seen in the 1960s. Idiosyncratic volatility increases in each quintile group from the 1950s until the 1990s, although it increases much more substantially in high- relative to low-IV stocks. In the last two decades, IV decreases across all quintiles. In contrast to the periods of rising IV, IV has fallen more rapidly in low- relative to high-IV stocks. The market capitalization of stocks is negatively related to IV and our aggregate volatility series are value weighted. Given this, we consider trends in each IV quintile's value-weighted contribution to aggregate IV. The high-IV quintile contributes the least at around 10% and this contribution is fairly stable. It is the low-IV quintile whose contribution time varies the most, with a peak of 50% and a low of around 10%, which is its current level. The middle three quintiles are now the dominant contributors to aggregate IV, with a contribution of about 80%.

Lastly, we investigate the characteristics of firms with different levels of IV and find that as IV increases, firm size and age decrease, whereas illiquidity increases. We confirm these findings in cross-sectional regressions. To obtain a complete picture of firm characteristics and IV, we sort stocks based on firm characteristics and confirm the earlier relationships observed between IV and size, age, and illiquidity. We see that value and growth firms have higher IV than stocks in the center of the book-to-market distribution and that in past return sorts, loser stocks have the highest IV followed by winners. When comparing IV across the low- and high-firm characteristic groups, we observe that size and illiquidity have the widest spread. Conversely, there are narrow spreads between the low and high groups for stocks sorted on age, institutional ownership, and book-to-market.

Bartram et al. (2019) attribute the fall in aggregate IV in the 2000s to listed firms becoming larger, older, and more liquid. We analyze the temporal change in these firm characteristics for our full sample and in IV-sorted quintiles and find that illiquidity decreases in all groups in the 2000s. Inflation-adjusted market capitalization and age increase in all but low-IV quintile stocks in the 2000s. These findings are consistent with the conclusions of Bartram et al. (2019).

The paper proceeds as follows. Section 2 presents our replication of key figures and tables in CLMX. Section 3 reports our out-of-sample findings in periods before and after post the CLMX sample. In Sections 4 and 5, we take a closer look at idiosyncratic volatility. Finally, Section 6 concludes.

2 Replication

2.1 Data

We replicate CLMX using the same data definitions and sample selection filters. We obtain daily and monthly firm-level return data from CRSP, including stocks traded on NYSE, AMEX, and Nasdaq. Campbell et al. (2001) study firms traded on NYSE, AMEX, and Nasdaq. They do not mention whether only ordinary stocks are included. As a result, we choose not to exclude stocks using the usual share code = 10, 11 filter. There is also no mention of how to treat delisting returns. Therefore, we do not adjust for delisted returns in order to replicate CLMX's study as closely as possible. Our sample period in this section follows CLMX, spanning July 1962 to December 1997. We use the 48-industry classification of Fama and French (1997) in analyses that require industry classification. Specifically, at the end of every month, we group stocks into one of the 48 industries based on the HSICCD industry classification of CRSP's data set.[3] Stocks that are not covered are allocated to an additional industry following CLMX. We download the monthly and daily risk-free rate from Ken French's data

[3] Campbell et al. (2001) do not mention whether they use SICCD or HSICCD in grouping stocks into industries. We find that the use of HSICCD produces industry volatility measures that are very similar to CLMX's.

library, which utilizes the one-month treasury bill rate from Ibbotson Associates. In this data library, the monthly risk-free rate is divided by the number of trading days in a month to obtain the daily risk-free rate. This rate is deducted from the daily return to obtain the daily excess return. Institutional holdings data is obtained from Thomson Reuters 13f database.

2.2 Methodology

We compute the sample market volatility (MKT_t), the sample industry volatility (IND_t), and the sample firm volatility ($FIRM_t$) using the same approach as CLMX. Unless otherwise mentioned, the sample volatilities are computed monthly (t), using daily return data in the same month (s).

MKT_t is computed as

$$MKT_t = \hat{\sigma}_{mt}^2 = \sum_{s \in t} (R_{ms} - \mu_m)^2, \quad (1)$$

where μ_m is the mean of the market return R_{ms} over the sample.[4] Eq. (1) above corresponds to Equation (17) in CLMX. Campbell et al. (2001) do not employ the value-weighted market return series (VWRETD) from the CRSP data set. They construct market returns as a weighted average using all firms in the sample (s) in a given period t. The market capitalization of a firm in period $t - 1$ is used as the weight and this weight is held constant within period t. They document that this approach yields an almost perfect correlation of 0.997. We obtain a similar correlation by using the same approach. Our constructed market returns have a correlation of 0.9986 with VWRETD from CRSP.

We undertake the following steps to compute IND_t. First, following Equation (6) in CLMX, we estimate the following return decomposition equation

$$R_{it} = R_{mt} + \epsilon_{it}. \quad (2)$$

[4] In this equation, the use of a raw return or an excess return does not make a difference, as the risk-free rate will cancel itself out.

Eq. (2) defines ϵ_{it} as the difference between the industry excess return R_{it} and the market excess return R_{mt}. For volatility in industry i, we sum the squares of the industry-specific residual in Eq. (2) within a period t

$$\hat{\sigma}^2_{\epsilon it} = \sum_{s\epsilon t} \epsilon^2_{is}. \quad (3)$$

Eq. (3) (Equation (18) in CLMX) estimates the sample industry volatility for each of the 49 industries. We subsequently average industries, following Equation (19) in CLMX as follows

$$IND_t = \sum_i w_{it} \hat{\sigma}^2_{\epsilon it}, \quad (4)$$

where w_{it} is the total market capitalization of an industry in period t−1, following the weighting scheme in computing market returns and volatility. $\hat{\sigma}^2_{\epsilon it}$ is the sample volatility of industry i in period t.

The sample firm volatility is computed in the following manner. First, the following firm return decomposition (Equation (10) in CLMX) is estimated

$$R_{jit} = R_{it} + \eta_{jit}, \quad (5)$$

where R_{jit} is the excess return of stock j, R_{it} is the excess return of industry i, and η_{jit} is the return difference between stock j and the industry i to which stock j belongs. Firm-specific volatility is constructed in a similar way to industry volatility. We subsequently sum the squares of the firm-specific residual from Eq. (5) above, following Equation (20) in CLMX

$$\hat{\sigma}^2_{\eta jit} = \sum_{s\epsilon t} \eta^2_{jis}. \quad (6)$$

Next, we compute the weighted average of the firm-specific volatilities within an industry, following Equation (21) in CLMX

$$\hat{\sigma}^2_{\eta it} = \sum_{j\epsilon i} w_{jit} \hat{\sigma}^2_{\eta jit}, \quad (7)$$

where w_{jit} is the market capitalization of stock j in period $t-1$ and $\hat{\sigma}^2_{\eta jit}$ is the sample firm-specific volatility in period t. Lastly, we average $\hat{\sigma}^2_{\eta it}$ over industries to obtain a measure of average firm-level volatility, $FIRM_t$ as follows

$$FIRM_t = \sum_i w_{it} \hat{\sigma}^2_{\eta it}. \quad (8)$$

In summary, we follow CLMX to decompose the return of each individual stock into the market-wide component, along with industry-level and firm-specific residuals. Volatility measures are estimated from the decomposition of the three components of returns. An advantage of this approach is that it does not require the estimation of betas or covariances for industries or firms.

2.3 Replication Results: Trends in Volatility over Time

A key aim of this paper is to replicate the main results in CLMX, which documents that firm-specific idiosyncratic volatility exhibits an upward trend. We first conduct the augmented Dickey and Fuller (1979) unit root ρ-tests and t-tests for MKT, IND, and FIRM, following Table II of CLMX. Panel A of Table 1 reports our replicated figures; Panel B tabulates the figures from CLMX. A consistent number of lags are used in all panels to ensure comparability.

Campbell et al. (2001) do not tabulate p-values associated with these statistics. They report the 5% critical values for these statistics and conclude that the hypothesis of a unit root is rejected for all three volatility series at the 5% level at least. We draw the same conclusion based on the p-values in parentheses of Panel A. The p-tests and t-tests for our volatility series have p-values that are less than 1%. This finding demonstrates that the hypothesis of a unit root for all three volatility series is rejected at the 1% level. The results remain similar whether a deterministic time trend is allowed or not, and regardless of whether the crash in October 1987 is down-weighted.

[Table 1 about here]

We proceed to replicate Table III and part of Table I of CLMX, which contain descriptive statistics and linear trends for MKT, IND, and FIRM. The statistics considered for each volatility series are (1) annualized mean, (2) annualized standard deviation, (3) annualized standard deviation based on detrended volatility series,[5] (4) linear trend coefficient, (5) PS-statistic of Vogelsang (1998) (t-PS),[6] and (6) first order autocorrelation. The autocorrelations for the daily series are reported in Table I of CLMX. Our replicated results, using the same sample period, are tabulated in Panel A of Table 2. Panel B reports the original results from CLMX. Our descriptive statistics and linear trend coefficients are very close to those of CLMX. For instance, the average of MKT, IND, and FIRM that we compute for the daily series are 1.464, 0.95, and 6.734, respectively in Panel A. In CLMX, these values are 1.542, 1.032, and 6.436. The descriptive statistics on standard deviation, autocorrelation, and linear trends in Panels A and B are also very close to one another, showing that we are successful in replicating the key figures in CLMX. We compare our volatility series to CLMX's; the correlations between our MKT, IND, and FIRM and theirs are 0.9985, 0.9256, and 0.9966, respectively.[7] The near perfect correlations for MKT and FIRM indicate that our decision to include all stocks and not filter by share code, and to ignore delisting returns is consistent with CLMX. The lower correlation with IND is likely due to changes in industry classifications over time.

[Table 2 about here]

For the IND and FIRM series created using weekly returns, monthly returns, and the equal-weighted (EW) approach, CLMX document that the raw series and the down-weighted crash series produce identical descriptive statistics and linear trend patterns. Upon closer inspection, we manage

---

[5] Statistically, several techniques can be used to detrend a time series; CLMX do not indicate the technique used for this purpose. We detrend the volatility series by deducting the predicted volatility figure (from OLS) from the raw volatility figure.

[6] Following CLMX, we employ the techniques in Vogelsang (1998) to detect linear time trends. The benchmark model is defined as $\gamma_t = \beta_0 + \beta_1 t + u_t$, where γ_t is the variable of interest and t represents the linear time trend. t-PS is the test statistic to examine whether $\beta_1 = 0$. The 5% and 10% critical values (two-sided) for t-PS are 2.152 and 1.720, respectively.

[7] Volatility series from CLMX are available on John Campbell's website at https://scholar.harvard.edu/campbell/data. A spreadsheet containing our volatility series and CLMX's is available in the supplementary materials of this paper.

to identify the cause. Campbell et al. (2001) down-weight the crash by replacing the volatility in October 1987 with the second largest volatility. While October 1987 is the month in which all three volatility series exhibit the largest fluctuation using daily returns, this is not the case using weekly and monthly returns, as well as when volatilities are equal-weighted. The purpose of down-weighting the crash is to mitigate the risk that the main results are driven by the largest outlier in the sample. As a result, we deviate from CLMX in our approach to down-weighting the crash. Replacing volatility in October 1987 with the second largest volatility causes some of the volatility series to remain unchanged because, in some instances, October 1987 is the month with the second largest volatility. We choose to replace the month with the largest volatility, regardless of whether it is October 1987, with the second largest volatility. A direct consequence of this approach is that the raw volatility series and down-weighted crash series will not produce identical descriptive statistics, which is different from CLMX.

Figure 1 illustrates the trends in MKT, IND, and FIRM over the 1926 to 2017 period. Volatility series estimated each month using daily data are presented in Panel A. The series are reported as annualized standard deviations. Panel B presents the backward 12-month moving average lines of the three volatility series. In the CLMX period (1963 to 1997), FIRM is higher than MKT and IND in general. MKT and IND tend to move closely with each other and do not exhibit a clear increasing or declining trend. On the contrary, FIRM follows an upward trend, especially towards the end of the CLMX period. The moving average lines demonstrate that both MKT and IND are slow moving. In both panels, an upward trend is observed in FIRM in the CLMX period. This is consistent with the evidence presented in Figures 4 to 6 in CLMX.

[Figure 1 about here]

Figure 2 plots the average R^2 statistic estimated from the market model. Following CLMX, we estimate the market model for each stock using five years of monthly data, using the NYSE-AMEX-Nasdaq composite index as the market index. Next, we compute the value-weighted and equal-weighted R^2 measures across all stocks. The equal-weighted measure reproduces the bottom panel of Figure 5 in CLMX. The pattern over the 1962 to 1997 period is largely consistent with CLMX, whereby R^2 tends to decline. This corroborates the finding of an upward trend in firm-specific volatility in CLMX.

[Figure 2 about here]

Figure 3 plots the excess standard deviation of portfolios comprising varying numbers of randomly selected stocks. It replicates Figure 6 of CLMX. Excess standard deviation is calculated by subtracting the standard deviation of an equally weighted index of all stocks from the portfolio's standard deviation. For the 1962 to 1997 period, the findings are consistent with CLMX. Excess standard deviations increase for all portfolio groups in Panel A. In Panel B, excess standard deviations are clearly highest for the 1986 to 1997 period. This implies that, for the CLMX period, the number of stocks required for a diversified portfolio has been increasing over time.

[Figure 3 about here]

2.4 Replication Results: Covariation of Market, Industry, and Firm Volatility

We next turn our attention to analyzing the relation between MKT, IND, and FIRM by reproducing Tables V and VI of CLMX. In these tables, the volatility series are monthly, created using daily return data and with a down-weighted crash. Table 3 documents the correlations for both the raw series and the detrended series. Our replicated results in Panel A are qualitatively similar to CLMX's original results in Panel B. Both panels indicate that market, industry, and firm volatilities are highly correlated regardless of whether the series are detrended or not. To determine the relative importance of market, industry, and firm volatility in a typical stock, we decompose the mean of these volatilities. Following CLMX, we define the volatility of a typical stock as

$$\sigma_{rt}^2 = MKT_t + IND_t + FIRM_t. \tag{9}$$

From this equation, we compute the mean proportion of each volatility (i.e., MKT, IND, and FIRM) relative to total volatility, σ^2, as reported in Table 4. Both the replicated and original results show that FIRM is the largest component of the volatility of a typical stock, with a mean proportion in excess of 70%.

[Tables 3 and 4 about here]

Table 4 also decomposes the variance of volatility via a covariance matrix that consists of MKT, IND, and FIRM.

$$1 = \mathrm{Var}(MKT_t)/\mathrm{Var}(\sigma^2_{rt}) + \mathrm{Var}(IND_t)/\mathrm{Var}(\sigma^2_{rt}) + \mathrm{Var}(FIRM_t)/\mathrm{Var}(\sigma^2_{rt})$$
$$+ 2\mathrm{Cov}(MKT_t,IND_t)/\mathrm{Var}(\sigma^2_{rt}) + 2\mathrm{Cov}(MKT_t,FIRM_t)/\mathrm{Var}(\sigma^2_{rt})$$
$$+ 2\mathrm{Cov}(IND_t,FIRM_t)/\mathrm{Var}(\sigma^2_{rt}). \quad (10)$$

This decomposition indicates the sources of the time-series variation in total volatility. Consistent with CLMX, we report that most total volatility variation arises from variation in MKT and FIRM, while IND is relatively stable over time. FIRM variance and the covariation of MKT and FIRM accounts for 62.7% of the total time-series variation in volatility. This is followed by MKT variance at 14.1% and the covariation of FIRM and IND, which is 13.7%.

2.5 Replication Results: Cyclical Behavior of Volatility Measures

Table 5 replicates Table IX in CLMX and examines the ability of volatility components to predict GDP growth. The OLS regression outputs with GDP growth (GDP_t) as the dependent variable are reported. All independent variables are lagged by one quarter. The three volatility measures are value-weighted and constructed from daily data. They are also linearly detrended and time-aggregated to a quarterly frequency.

Panel A reports our replication over the original sample period and CLMX's results are in Panel B. Both our regression coefficients and R^2 are similar to CLMX. Each individual volatility measure is negatively significant when it is the only volatility measure in the regression. The volatility measures become insignificant when pairs of volatility series are included in the regression in all but one instance.

[Table 5 about here]

3 Out-of-Sample Analysis

To examine whether the patterns in the volatility series vary over time, we implement out-of-sample analysis in this section. The sample period of CLMX starts in July 1962 due to data availability at the time of the study. With the broader coverage of daily data, we can extend the start of the sample back to July 1926. As a result, we repeat the replication analysis for the July 1926 to June 1962 and the January 1998 to December 2017 periods. The July 1926 to June 1962 period is denoted as the pre-CLMX period. Results are presented in Panel A in Tables 6 to 9. Analysis of the post-CLMX period (January 1998 to December 2017) is presented in Panel B in Tables 6 to 9.

Table 6 shows that the three volatility series are stationary in the pre- and post-CLMX periods, which is in line with the results over the CLMX period. Unlike the results in Table 2, the linear trends in volatility are negative in both the pre- and post-CLMX periods in Table 7. This is in stark contrast to the finding of a strong positive trend in CLMX. The first order autocorrelations are higher in Table 7 than in the CLMX period in Table 2; in many cases they are considerably higher.

Correlations and the decomposition of the volatility series in Tables 8 and 9 remain similar to results over the CLMX period. One notable difference though is that, in Table 9, FIRM's contribution to total volatility is around 60%, whereas it is around 75% during the CLMX sample period. This decline is offset by an increase in MKT's contribution from around 15% in Table 4 to 25% in Table 9.

[Tables 6 to 9 about here]

Consistent with the decline in aggregate IV, R^2 from the market model exhibits an increasing trend in the post-CLMX period in Figure 2, particularly until 2013. It has declined again, though, in the past few years. Figure 3 shows that the number of stocks required to achieve a diversified portfolio has fallen in the 20 years after CLMX. To illustrate, a 20-stock portfolio has an excess standard deviation of 10.4%, 6.2%, and 3.4% in the 1986 to 1997, 1998 to 2008, and 2009 to 2017 periods, respectively. Excess standard deviation has started increasing again though from 2011, albeit moderately, in Panel A.

Figure 1 visualizes the trends in the three volatility series. In the pre-CLMX period, MKT, IND, and FIRM all reach their historical peaks during the Great Depression. After that, all three series revert to their normal levels. In the post-CLMX period, MKT and IND remain close to one another. In contrast to the CLMX period, FIRM is no longer considerably higher than MKT and IND. Apart from a large spike in the early 2000s and the financial crisis of 2008, FIRM has been considerably lower and more stable in the recent two decades. As a result, IV in the U.S. equity market does not exhibit an increasing trend in either the pre- or post-CLMX periods, suggesting that CLMX's finding is sample-specific.

Our finding of a negative trend and the decrease in FIRM after the Great Depression in the pre-CLMX period corroborates the evidence in Fink et al. (2010). The decline in FIRM in the post-CLMX period is in line with Fink et al. (2010), Brandt et al. (2010), Bekaert et al. (2012), Kang et al. (2014), Campbell (2018), and Bartram et al. (2019). Campbell et al. (2001) propose a number of explanations for the increase in FIRM, including a larger number of focused companies, a tendency for firms to issue equity earlier in their life cycle, changes in executive compensation schemes, development of financial technology, and increases in institutional ownership.

The increase in FIRM that CLMX document has led to a large strand of literature that explores the proposed explanations. Xu and Malkiel (2003) and Bennett et al. (2003) relate the upward trend in idiosyncratic volatility until 1998 to the increasingly important role of institutional investors. Pastor and Veronesi (2003) and Wei and Zhang (2006) link the increase in idiosyncratic volatility to the upward trend in the volatility of firm profitability. Brown and Kapadia (2007) argue that new listings of riskier companies contribute to this upward trend. Based on a classic corporate finance model, Cao et al. (2008) posit that growth options explain the trend in idiosyncratic volatility.

Over the 1964 to 2003 period, Irvine and Pontiff (2009) conjecture that the increase in idiosyncratic volatility is driven by intense competition in the economy that boosts idiosyncratic volatility in fundamental cash flows. Brandt et al. (2010) document a spike in idiosyncratic volatility at the end of CLMX's period and reversal to a normal level by 2003. They attribute this to low-priced stocks with high retail ownership. Fink et al. (2010) extend the period to 2006 and observe that the declining trend continues. They postulate that firm age explains the large spike in idiosyncratic risk. The downward trend is found to continue to the end of 2007, followed by an upward spike in 2008 in Kang et al. (2014). Instead of focusing on the time trend in the population of stocks, Kang et al. (2014) focuses on the cross-sectional dynamics of stocks with extreme idiosyncratic volatility, which are found to be largely driven by hedge fund holdings. Bartram et al. (2019) consider why IV has fallen since the 2000s and conclude that it is due to U.S. listed firms becoming larger, older, and more liquid.

Table 10 examines the ability of the three volatility series to predict GDP growth out-of-sample. In the pre-CLMX period, none of the volatility series predict GDP growth as either the sole or joint predictor. After CLMX, the power of the three series to predict GDP growth individually is similar to the original results. In contrast to the CLMX period in which the volatility series lose statistical significance when included together, IND remains statistically significant when regressed with either MKT or FIRM. IND appears to be a stronger predictor of GPD growth more recently.

[Table 10 about here]

4 Idiosyncratic Volatility Using Asset Pricing Models

Recent advancements in asset pricing give rise to a large number of asset pricing factors that are related to the cross-sectional variation in stock returns. In line with the literature, we estimate firm-specific volatility as IV, which is the standard deviation of the residuals, using the market model; the Fama and French (1993) three-factor model; and the Fama and French (2015) five- and six-factor (five factors augmented with the momentum factor) models. We denote them as IV-MM, IV-FF3, IV-FF5, and IV-FF6, respectively. Taking IV-FF3 as an example and following Ang et al. (2006), IV-FF3 is measured by regressing daily stock returns in excess of the risk-free rate on the three factors (MRP, SMB, and HML) in the same month.[8] IV-FF3 is computed as the standard deviation of the residuals from the regression. This procedure is repeated each month to generate stock-month estimates of IV-FF3. IV-FF5 is estimated in a similar fashion using the Fama and French (2015) five-factor model, which includes the MRP, SMB, HML, RMW, and CMA factors. IV-FF6 is calculated using a six-factor model that includes the MRP, SMB, HML, RMW, CMA, and UMD factors. For each asset pricing model, the monthly value-weighted average IV across all stocks is computed to obtain an aggregate measure of monthly idiosyncratic volatility. Following CLMX, the weight of each stock is based on its market capitalization in the previous month.

Table 11 presents the correlations among MKT, IND, FIRM, IV-MM, IV-FF3, IV-FF5, and IV-FF6 over the July 1963 to December 2017 period. July 1963 is the first month in which data for the Fama-French five- and six-factor models is available. The four IV measures estimated using asset pricing models are strongly correlated with each other, evidenced by correlations ranging from 0.981 to 0.999. Idiosyncratic volatility measures using asset pricing models are also highly correlated with FIRM, with the correlations ranging from 0.973 to 0.985. This indicates that IV estimated using asset pricing models captures aggregate idiosyncratic volatility in a fashion very similar to CLMX's FIRM measure. Given the near perfect correlations between IV-FF3, IV-FF5, and IV-FF6, for the rest of the paper, IV-FF3 is adopted as IV from the multi-factor asset pricing models.

[Table 11 about here]

[8] We obtain the Fama-French factors from Ken French's website. Firms that trade for less than 15 days in a month are excluded.

Figure 4 displays the trends in FIRM, IV-MM, and IV-FF3. IV-MM is very close to IV-FF3 in magnitude. FIRM is, in general, slightly higher than both IV-MM and IV-FF3. All three series share very similar trends, which is also evidenced in their 12-month moving average lines in the lower panel. In the post-1963 period, spikes in FIRM, IV-MM, and IV-FF3 are observed in 1987, the 1998 to 2000 period, as well as in 2008. There is no upward trend in the firm-specific volatility series in the pre- or post-CLMX period. On the contrary, the series tend to decline during these periods.

[Figure 4 about here]

Table 12 presents the levels of the volatility series, including MKT, IND, and all IV measures in subperiods grouped roughly by decade. After a decline following the Great Depression, MKT, IND, and the IV measures began increasing in the 1950s. Except for a large spike in MKT in the 2000s, the IV measures have been increasing at a more rapid rate than both MKT and IND, consistent with Figure 1. MKT and IND peaked in the 2000s and have declined in the most recent period, from 2011 to 2017. The IV measures peaked in the 1990s and have declined in the latest two periods. In the most recent period, from 2011 to 2017, MKT is at levels last seen in the 1980s and 1990s. For IND, it is at levels similar to the 1970s and 1980s. With the IV measures, their levels correspond to those last seen in the 1960s. It is clear that in the post-CLMX period, a declining trend is observed in all IV series. In contrast, MKT and IND are now at levels that are similar to periods within the CLMX sample.

[Table 12 about here]

Thus far, we have only considered the mean of our idiosyncratic volatility series. Figure 1 of Kang et al. (2014) highlights some interesting patterns in other cross-sectional moments for the 1963 to 2008 period. We reexamine this analysis using IV-FF3 for an extended period from 1926 to 2017. Figure 5 reports the value-weighted cross-sectional standard deviation, skewness, and kurtosis of monthly stock-level IV-FF3. For clarity, we plot the backward 12-month moving averages of these series. In Panel A, standard deviation decreases following the Great Depression and then steadily increases from around 1950 until the mid-1990s. It then begins increasing more rapidly and it spikes during the dot-com crash, the financial crisis, and around 2016. It has been at much higher levels over the past 20 years. Skewness and kurtosis in Panels B and C share similar patterns in that they decline following the Great Depression and have been generally rising since. This is particularly so with skewness.

When comparing these time-series patterns with the trends in the aggregate level of IV, there is an interesting contrast between the CLMX and post-CLMX period. There is an increasing trend in all three plots during the CLMX period in line with the increase in the aggregate level of IV. In the post-CLMX period and, in particular, following the financial crisis, a disconnect has arisen. The aggregate level of IV after the financial crisis is relatively low and yet the dispersion in stock-level IV is relatively high. Stock-level IV has become much more cross-sectionally disperse, positively skewed, and kurtotic in recent times. Investigating this phenomenon is a potentially promising area for future research. Additionally, these observations help motivate our closer examination of IV in the next section.

[Figure 5 about here]

5 A Closer Look at Stock-Level Idiosyncratic Volatility

The results thus far focus on the aggregate volatility series. This section explores the volatility pattern and characteristics of stocks in different groups. Doing so allows us to take a closer look at IV in the U.S. equity market. First, we investigate the contribution to overall IV by stocks from different IV groups. In the previous sections, five firm-specific volatility measures were examined, including FIRM, IV-MM, IV-FF3, IV-FF5, and IV-FF6. FIRM can only be calculated at the aggregate level and hence is not a stock-level IV measure. Conversely, while IV-FF5 and IV-FF6 are constructed at the individual stock level, they are available over a shorter period due to the availability of the asset pricing factors. Both IV-MM and IV-FF3 are good stock-level IV measures over the longest period, beginning in 1926. Given that IV-FF3 is the conventional measure of IV in the literature, it is the one we employ for the remainder of the paper.

Table 13 reports the level of IV-FF3 quintile-sorted portfolios over the same subperiods as Table 10. Stocks are ranked into quintiles based on IV-FF3 at the end of each month. Following declines after the Great Depression, IV monotonically increases across all quintiles from the 1950s until the 1990s. It increases more markedly though in stocks with higher, relative to lower, IV. For example, the low-IV quintile increases by 75% over this period, whereas the high-IV quintile increases by 212%. Idiosyncratic volatility then declines in the last two subperiods across all groups. Of note, the decline is more substantial in the low-IV, relative to the high-IV, groups. This indicates that IV is falling more rapidly in stocks with lower IV. To illustrate, the lowest and second lowest IV quintiles record their lowest IV levels in the most recent period, from 2011 to 2017; this is not the case in the other three quintiles.

[Table 13 about here]

Figure 6 presents details of IV-FF3 in quintile groups. Panel A plots the level of IV-FF3 across five IV-FF3-sorted portfolios. The overall trend is similar in all quintiles. The high-IV quintile tends to fluctuate more than the other quintiles though, especially in crisis periods. For example, during the Great Depression, circa 1930, all quintiles experience a large increase in IV. The most considerable increase is documented in the high-IV quintile, which peaks off the scale at 895% per annum in August 1932. The difference in IV between the low- and high-IV quintiles has been increasing from the 1950s until the dot-com crash in the early 2000s. In the calm market periods before and after the 2008 financial crisis, this spread has narrowed to a level last seen in the 1960s.

[Figure 6 about here]

To gain a better understanding of stocks in different IV quintiles, Table 14 presents their basic characteristics, including market capitalization (size), age (in years), the Amihud (2002) illiquidity ratio, institutional ownership, book-to-market ratio (BM), and momentum over the last 12 months.

As discussed in Section 3, studies including Xu and Malkiel (2003), Cao et al. (2008), Brandt et al. (2010), and Bartram et al. (2019) propose different explanatory variables for the trend in IV. Taking guidance from the prior studies that document the cross-sectional determinants of IV that are central to explanations of the aggregate IV trends, the aforementioned variables are chosen to provide an independent analysis in the latest sample period. Size, age, and illiquidity are key determinants in the most recent paper by Bartram et al. (2019). Institutional ownership is the focus of the studies by Xu and Malkiel (2003) and Bennett et al. (2003). Book-to-market is commonly analyzed when considering cross-sectional determinants of IV such as in Brandt et al. (2010). Brandt et al. (2010) also consider momentum, and we follow suit given that our regression specification most closely follows theirs.

Accounting data, including the book value of assets and common equity, are obtained from the Compustat annual data file. Institutional ownership data is sourced from the CDA/Spectrum files maintained by Thomson Financial. Due to the availability of the institutional ownership data, this analysis starts in April 1980. Size and age decrease as IV increases, whereas illiquidity and book-to-market increase with IV.[9] There is an inverse U-shaped relation between both momentum and institutional ownership with IV.

[Table 14 about here]

Panel A of Figure 6 shows that IV in the high quintile group is considerably higher than in the other quintiles. Table 14 shows that the market cap of stocks in this group is very small relative to the other groups. This raises the question of how much stocks across the cross-sectional distribution of IV contribute to aggregate market-level IV, which is value-weighted. To assess this, and similar to Kang et al. (2014), we consider the contribution to aggregate IV by each IV quintile in Panel B of Figure 6. These contributions are calculated by scaling a quintile's IV in a month by its market cap

[9] The negative relation between size and IV is also observed earlier in the sample from 1926 to 1979.

weight in the previous month and then representing these values as proportions out of 100%. Panel B shows that the high-IV group's contribution to aggregate IV has been fairly stable, hovering around 10% since 1926. It is the low-IV group, which is also the largest by value-weight, whose contribution to aggregate IV has fluctuated the most. Its contribution peaked around 50% in the 1930s and has fallen to around 10% on three occasions, which include the early 1980s, during the dot-com crash, and in the last years of the sample. This fall has been offset by increases in the contributions of the middle three quintiles, which are now the dominant contributors to aggregate IV. They are responsible for around 80% of the market's aggregate IV.

To extend the analysis of firm characteristics in IV groups in Table 14, we now explore via regression how firm characteristics relate to IV. We estimate the following regression on a monthly basis using the Fama-MacBeth technique

$$\ln(IV_{i,t}) = b_0 + b_1 \ln(IV_{i,t-1}) + b_2 \ln(size_{i,t-1}) + b_3 \ln(age_{i,t-1}) + b_4\, Illiq_{i,t-1} + b_5\, Inst_{i,t-1} + b_6 \ln(BM_{i,t-1}) + b_7\, Mom_{i,t-1} + \varepsilon_{i,t}, \qquad (11)$$

where $\ln(IV_{i,t})$ is the log of IV-FF3 of stock *i* in month *t*; $\ln(size_{i,t-1})$, $\ln(age_{i,t-1})$, and $\ln(BM_{i,t-1})$ represent the natural log of market capitalization, age, and book-to-market ratio of stock *i* in month *t-1*; $Illiq_{i,t-1}$ is the Amihud (2002) illiquidity ratio of stock *i* in month *t-1*; $Inst_{i,t-1}$ is the fraction of shares held by institutional investors of stock *i* in month *t-1*; and $Mom_{i,t-1}$ is the return of stock *i* from month *t*−13 to month *t*−3. We estimate the regression with and without the lag of IV and employing both equal-weighted and value-weighted Fama-MacBeth regressions. The value-weighted regressions cross-sectionally weight each firm-month observation by market capitalization, following Ang et al. (2009). The estimation period is April 1980 to December 2017 and the results are presented in Table 15.

In all regression specifications, IV is negatively related to size and age, and positively related to illiquidity. These findings are consistent with the firm characteristic patterns observed in the IV groups in Table 14. For institutional ownership, book-to-market, and momentum, the findings vary across the regression specifications. For example, institutional ownership is negatively (positively) related to IV in the equal- (value-) weighted regressions. Tables 14 and 15 show clear relations between size, age, and illiquidity with IV that are consistent both with prior findings and intuition. For the other three variables, the relations are more nuanced. Taking momentum as an example, we know that both losers and winners tend to have higher volatility than stocks in the center of the distribution. We demonstrate this next in Table 16.

[Table 15 about here]

Next, we explore trends in IV in different characteristic-sorted groups. In contrast to the analysis in this section thus far, where we examined stocks in IV groups, we now sort stocks into characteristic-based groups. The characteristics of interest are those analyzed earlier. Table 16 reports the level of IV in quintiles sorted on size, age, illiquidity, institutional ownership, book-to-market, and momentum. It shows that as size and age increase, IV decreases and that as illiquidity increases, IV increases. There is a decreasing trend in IV as institutional ownership increases, although the relation is not monotonic. With momentum, losers have the highest IV followed by winners. With book-to-market, the relation to IV differs from the earlier period in Panel A to the latter period in Panel B. In Panel A, IV increases monotonically across the book-to-market quintiles. In Panel B, value firms have the highest IV followed by growth firms. The widest dispersion between the low and high groups occurs with size and illiquidity, where the spread is around 40% per annum. In contrast, the spreads from low to high for the other groups are narrower. For example, in Panel B they range from 3% for book-to-market to 13% for age.

[Table 16 about here]

The time-series movements in the level of IV across size, age, illiquidity, institutional ownership, book-to-market, and momentum quintiles are plotted in Panels A to F of Figure 7. For comparability, the maximum value of the y-axis in all panels is 1.6, which equates to a standard deviation of 160% per annum. Consistent with Table 16, it is size in Panel A, illiquidity in Panel C, and to a lesser extent momentum in Panel F that have the greatest variability in IV across quintiles. The spread across quintiles is much narrower with age in Panel B, institutional ownership in Panel D, and particularly with book-to-market in Panel E. The size and illiquidity plots are similar and both show a clear ordering and increase in IV from large to small quintiles and liquid to illiquid quintiles. Both the large and liquid groups' IV hovers around 20% except during turbulent market periods, when it spikes. The IV spread between small and large, and liquid and illiquid groups has been increasing from the 1950s to the 1990s and has been tending to decline since. In the calm pre- and post-financial crisis period, this spread is at levels similar to the 1960s to 1980s. With momentum, loser stocks have the highest temporal variability in IV and they generally have the highest level, although there are periods where winner stocks have the highest IV.

For age, although the spread is narrower across groups, there is generally an increase in IV levels from older to younger firms. For the most part, the youngest firms have the highest IV, whereas the oldest firms always have the lowest IV. With institutional ownership, although the spread is narrow, there is more variation in terms of which group has the highest IV. For most of the 1980s and 1990s, it is the second lowest group that has the highest IV. After the dot-com crash, it is the lowest and highest institutional ownership groups that have the highest IV. The differences in IV across the groups, though, particularly in recent times, is quite low. Similar to institutional ownership, the spread across book-to-market groups is low. Except for a handful of occasions, it is either the value or growth group that has the highest IV. In summary, the widest variation in IV across characteristic-sorted groups is for size and illiquidity, and to a lesser extent, momentum. Although the spreads across the size and illiquidity groups have narrowed in recent times, they remain considerably wider than all but the momentum groups.

[Figure 7 about here]

Bartram et al. (2019) find that the decrease in aggregate IV in the post-CLMX period is due to listed firms becoming larger, older, and more liquid. To investigate this, we examine the time-series trends in these firm characteristics across the full sample and in IV-sorted quintiles. Table 17 reports inflation-adjusted market capitalization, firm age, and illiquidity for the full sample and in IV quintiles in subperiods grouped roughly by decade. For the full sample, and consistent with Bartram et al. (2019), size and age increase and illiquidity decreases in the post-CLMX period. We observe the same trend in all IV quintiles for illiquidity and in IV quintiles two to five for size and age. In contrast, in the low-IV group, size decreases in the 2011 to 2017 period and age decreases in both subperiods in the 2000s. Recall that from Figure 6b, though, the low-IV quintile group's contribution to aggregate IV is only around 10% in the past decade. In sum, this analysis confirms the finding of Bartram et al. (2019) that listed firms are larger, older, and more liquid in the 2000s. In addition, we show that this is also the case across the majority of the IV-sorted distribution. We thus present supportive evidence for their conclusion that the change in these firm characteristics is responsible for the decline in aggregate IV in the 2000s.

[Table 17 about here]

6 Conclusion

This paper replicates the findings of CLMX, who investigate trends in the volatility of stocks in the U.S. market over the 1962 to 1997 period. We are successful in replicating their key findings by utilizing their disaggregated approach to investigating volatilities at the market, industry, and individual stock levels. We confirm that aggregate idiosyncratic volatility increases over their sample period. We conduct out-of-sample testing by investigating the periods before (1926 to 1962) and after (1998 to 2017) CLMX. In contrast to the CLMX period, idiosyncratic volatility did not increase during these periods; it declined.

In addition to the disaggregated approach to estimating volatilities in CLMX, we use asset pricing models to estimate idiosyncratic volatility. We document that IVs estimated with a variety of Fama-French–style models and the market model are very similar to CLMX's IV measure and to each other. Using asset pricing models to estimate IV at the stock level, we undertake a series of further analyses to more closely examine IV. We examine trends in IV and how IV relates to various firm characteristics for a more complete picture of IV and its times-series trends.

The decline in aggregate IV following the dot-com crash, with the exception of an episodic spike around the financial crisis, is an interesting counterpoint to the increase during the CLMX sample. The difference in IV between low- and high-IV quintile groups has also fallen since the end of the CLMX period. So too has the difference in IV between small and large, and liquid and illiquid quintile groups. In cross-sectional analysis and consistent with prior research, IV is negatively related to size, age, and liquidity. Bartram et al. (2019) consider why IV has fallen since the 2000s and conclude that it is due to listed firms becoming larger, older, and more liquid. We confirm that firms have become larger, older, and more liquid in the post-CLMX period. In sum, our collective evidence on trends in IV and its relation to firm characteristics is consistent with Bartram et al.'s (2019) conclusion as to why IV has declined.

The low volatility levels that the market enjoyed after the financial crisis have ended abruptly with the COVID-19 pandemic. Once again, the market is in a high-volatility state with uncertainty around how long it will last. Coupled with this, listed firms and the macroeconomic environment continue to evolve. As a consequence, the aggregate level and the cross-sectional distribution of volatility will change and new trends will emerge. Examining trends in volatility and their determinants will likely remain a fruitful and important area of research for the foreseeable future.

References

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang. 2006. “The Cross-Section of Volatility and Expected Returns.” *Journal of Finance*. 61:259–299.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang. 2009. “High Idiosyncratic Volatility and Low Returns: International and Further U.S. Evidence.” *Journal of Financial Economics*. 91:1–23.

Amihud, Y. 2002. “Illiquidity and Stock Returns.” *Journal of Financial Markets*. 5:31–56.

Bartram, S. M., G. W. Brown, and R. M. Stulz. 2019. “Why Is There a Secular Decline in Idiosyncratic Risk in the 2000s?” *Working Paper*. Fisher College of Business.

Bekaert, G., R. J. Hodrick, and X. Zhang. 2012. “Aggregate Idiosyncratic Volatility.” *Journal of Financial and Quantitative Analysis*. 47:1155–1185.

Bennet, J. A., R. W. Sias, and L. T. Starks. 2003. “Greener Pastures and the Impact of Dynamic Institutional Preferences.” *Review of Financial Studies*. 16: 1203–1238.

Brandt, M. W., A. Brav, J. R. Graham, and A. Kumar. 2010. “The Idiosyncratic Volatility Puzzle: Time Trend or Speculative Episodes.” *Review of Financial Studies*. 23: 863–899.

Brown, G., and N. Kapadia. 2007. “Firm-Specific Risk and Equity Market Development.” *Journal of Financial Economics*. 84:358–388.

Campbell, J. Y. 2018. *Financial Decisions and Markets: A Course in Asset Pricing.* Princeton University Press, Princeton, NJ.

Campbell, J. Y., M. Lettau, B. G. Malkiel, and Y. Xu. 2001. “Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk.” *Journal of Finance*. 61:1–43.

Campbell, J. Y., and P. Perron. 1991. “Pitfalls and Opportunities: What Macroeconomists Should Know about Unit Roots.” *NBER Macroeconomics Annual*. 6:141–201.

Cao, C., T. Simin, and J. Zhao. 2008. “Can Growth Options Explain the Trend in Idiosyncratic Risk?” *Review of Financial Studies*. 21:2599–2633.

Dickey, D., and W. Fuller. 1979. “Distribution of the Estimators for Autoregressive Time Series with a Unit Root.” *Journal of the American Statistical Association*. 74:427–431.

Fama, E. F., and K. R. French. 1993. “Common Risk Factors in the Returns on Stocks and Bonds.” *Journal of Financial Economics*. 56:3–56.

Fama, E. F., and K. R. French. 1997. “Industry Costs of Equity.” *Journal of Financial Economics*. 82:153–193.

Fama, E. F., and K. R. French. 2015. “A Five-Factor Asset Pricing Model.” *Journal of Financial Economics*. 116:1–22.

Fama, E. F., and J. D. MacBeth. 1973. “Risk, Return, and Equilibrium: Empirical Tests.” *Journal of Political Economy*. 81: 607–636.

Fink, J., K. E. Fink, G. Grullon, and J. P. Weston. 2010. “What Drove the Increase in Idiosyncratic Volatility during the Internet Boom?” *Journal of Financial and Quantitative Analysis*. 45: 1253–1278.

Irvine, P. J., and J. Pontiff. 2009. “Idiosyncratic Return Volatility, Cash Flows, and Product Market Competition.” *Review of Financial Studies*. 22: 1149–1177.

Kang, N., P. Kondor, and R. Sadka. 2014. “Do Hedge Funds Reduce Idiosyncratic Risk?” *Journal of Financial and Quantitative Analysis*. 49: 843–877.

Newey, W. K., and K. D. West. 1987. “A Simple, Positive-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix.” *Econometrica*. 55: 703–708.

Pastor, L., and P. Veronesi. 2003. “Stock Valuation and Learning about Profitability.” *Journal of Finance*. 58: 1749–1789.

Shleifer, A., and R. W. Vishny. 1997. “The Limits of Arbitrage.” *Journal of Finance*. 52:35–55.

Vogelsang, T. 1998. “Trend Function Hypothesis Testing in the Presence of Serial Correlation.” *Econometrica*. 66:123–148.

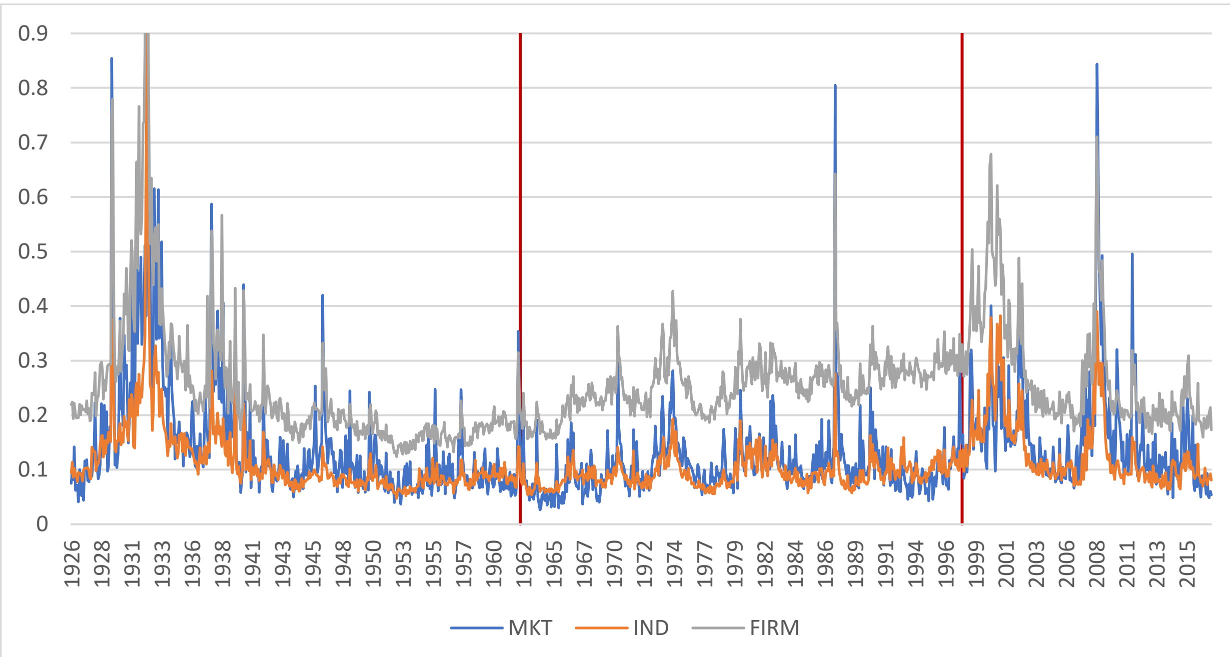
Wei, S. X., and C. Zhang. 2006. “Why Did Individual Stocks Become More Volatile?” *Journal of Business*. 79:259–292.

Xu, Y., and B. G. Malkiel. 2003. “Investigating the Behavior of Idiosyncratic Volatility.” *Journal of Business*. 76:613–644.

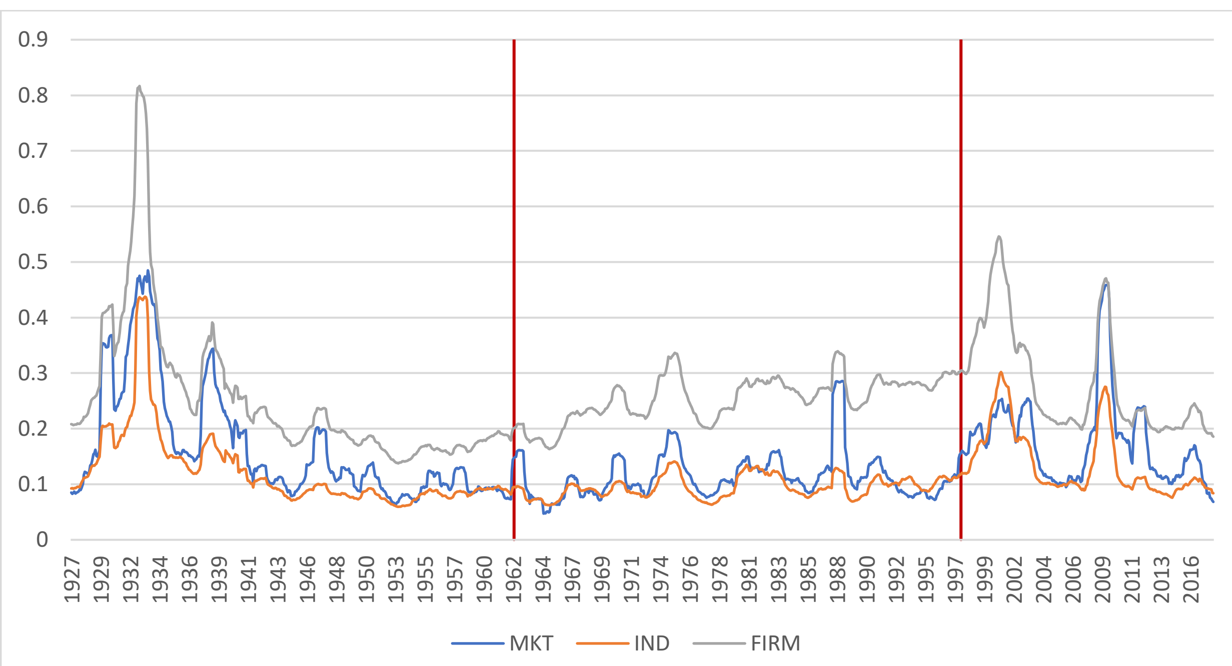
Figure 1: CLMX Volatility Series

Description: MKT, IND, and FIRM represent market-, industry-, and firm-level volatility computed from Eqs. (1), (4), and (8). The series are value-weighted and reported as annualized standard deviations. The sample period is July 1926 to December 2017. Panel A plots the unadjusted mean of the monthly volatility series and Panel B plots the backward 12-month moving averages of the series. The area between the red vertical lines represents the CLMX period.

Interpretation: Consistent with CLMX, FIRM increases over their sample period. Before and after their sample period, FIRM decreases. MKT and IND do not exhibit a time-series trend.



Panel A: Volatility Series



Panel B: Volatility Series, MA (12)

Figure 2: *R*-Squares from the Market Model

Description: This figure plots the value-weighted (R2-VW) and equal-weighted (R2-EW) average R^2 from the market model, estimated using the past 60 months of monthly data and employing data over the July 1926 to December 2017 period. The area between the red vertical lines represents the CLMX period.

Interpretation: *R*-squares have a decreasing trend from the start of the sample until the end of the CLMX period. They increase in the post-CLMX period until 2013 and then decline again. Excluding the Great Depression, these trends are broadly consistent with those in idiosyncratic volatility in that as IV increases, *R*-squares tend to decrease and vice versa.

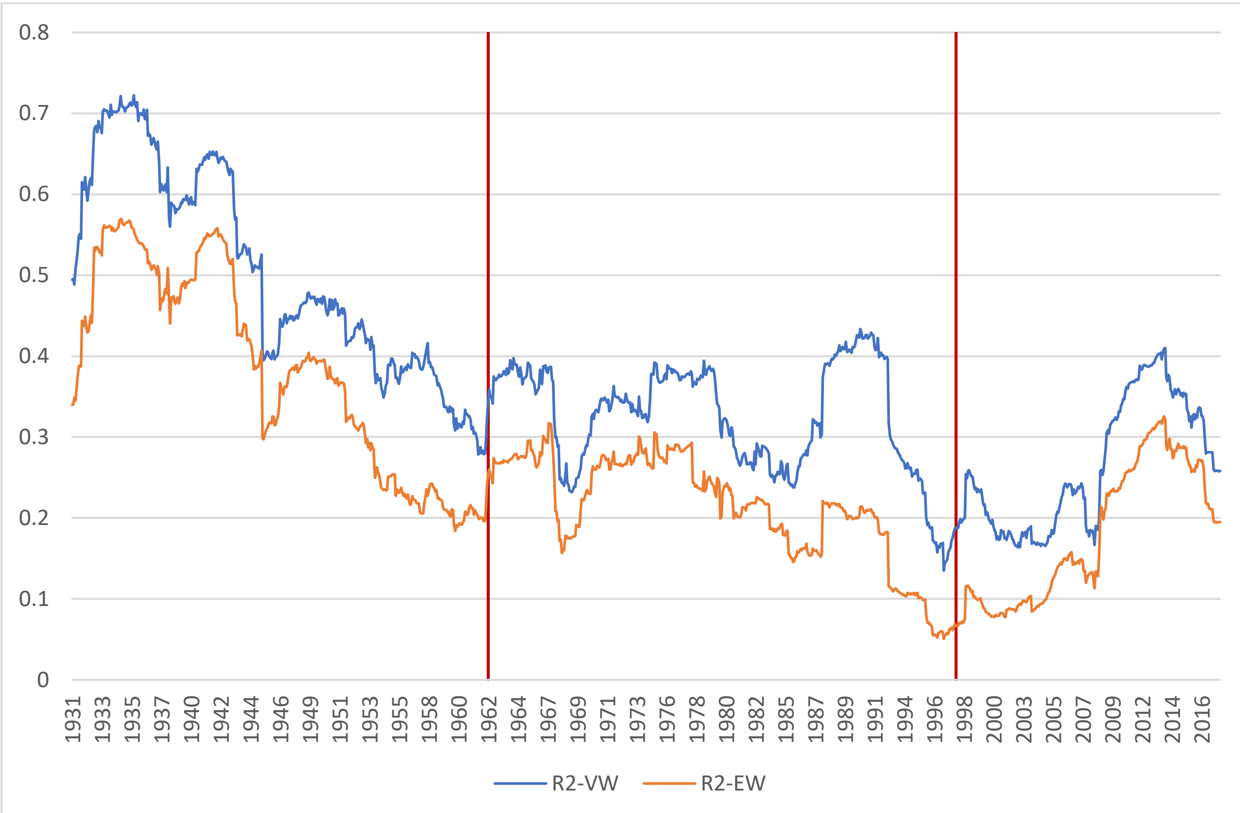
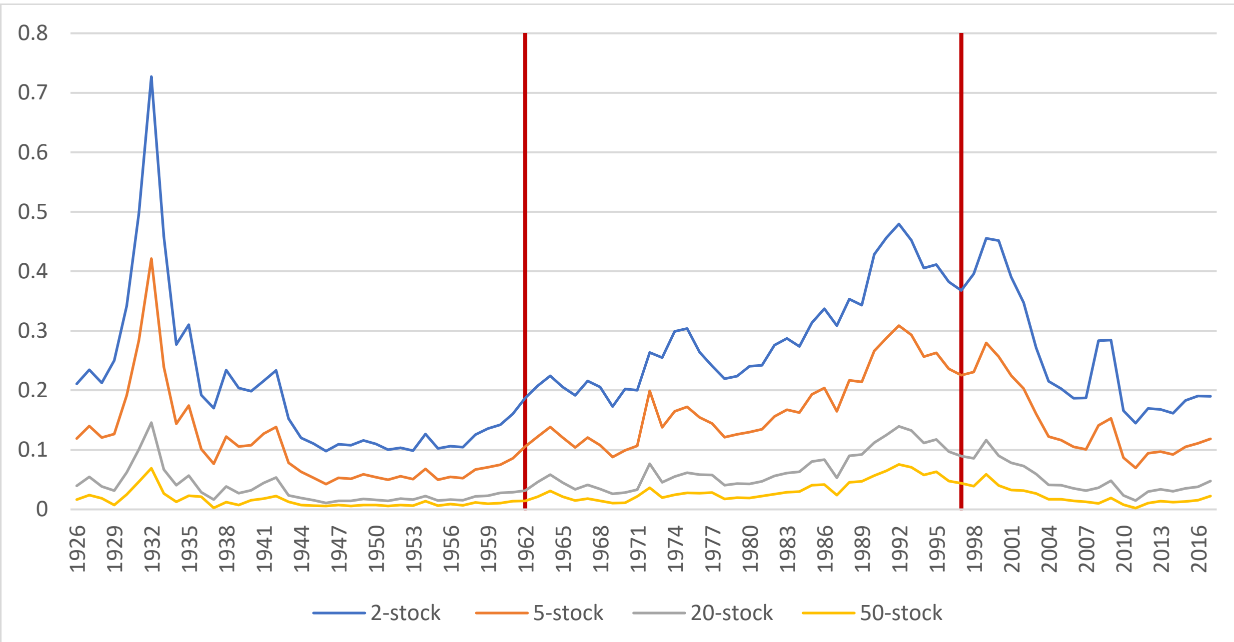


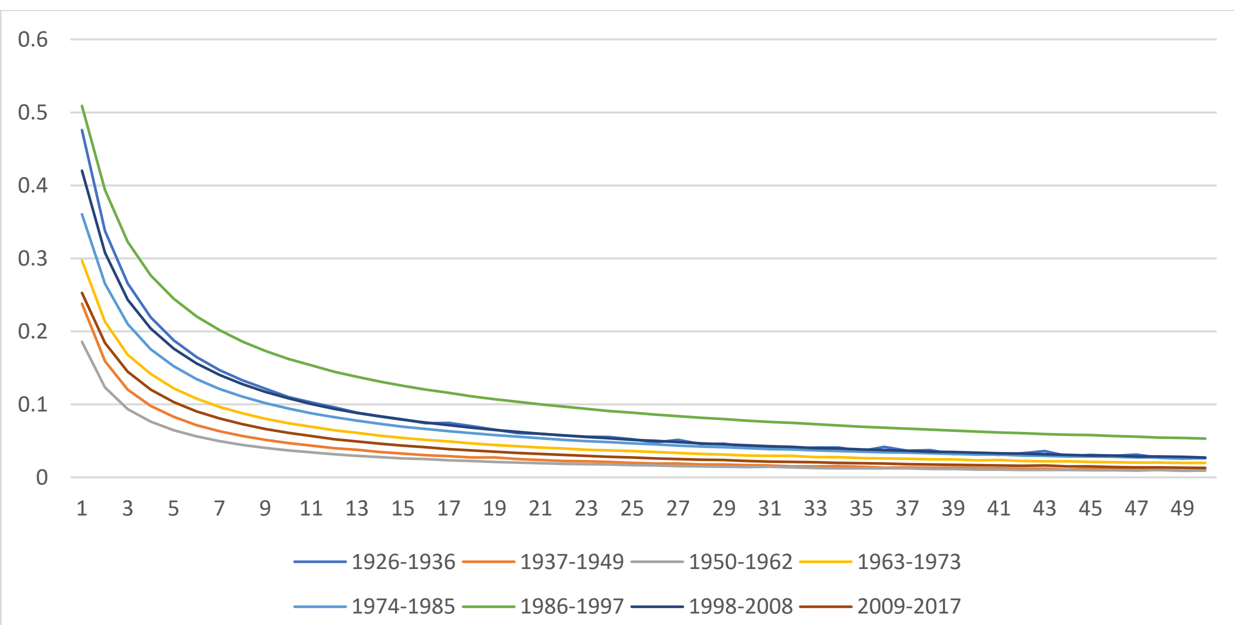
Figure 3: Excess Standard Deviation against Time and Number of Stocks

Description: The excess standard deviation of a portfolio is the difference between the portfolio's standard deviation and the standard deviation of an equally weighted index. Panel A plots annualized excess standard deviation against time. Excess standard deviation is calculated each year from daily data within the year for randomly selected portfolios containing 2, 5, 20, and 50 stocks. Panel B plots annualized excess standard deviation against the number of stocks in the portfolio for subperiods spanning 1926 to 2017. In Panel A, the area between the red vertical lines represents the CLMX period.

Interpretation: Excess standard deviation increases from the 1950s until the end of the CLMX period. It decreases in the post-CLMX period. An increase (decrease) in excess standard deviation suggests that the number of stocks required for a diversified portfolio increases (decreases).



Panel A: Excess Standard Deviation against Time

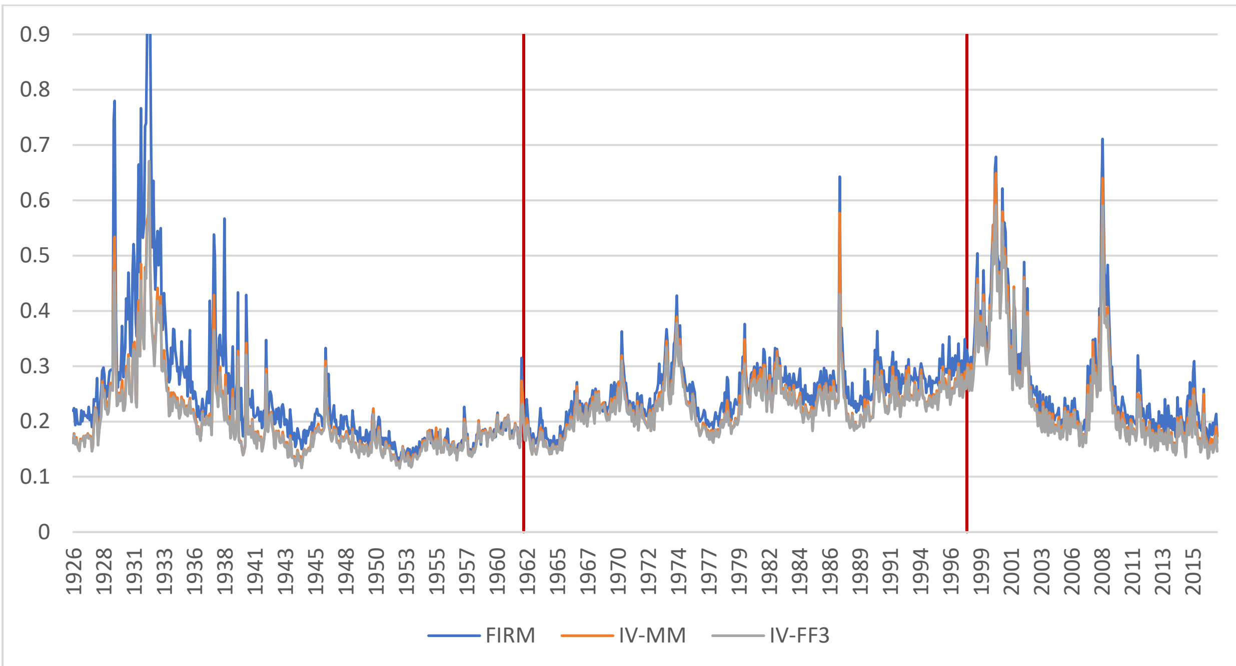


Panel B: Excess Standard Deviation against Number of Stocks for Subperiods

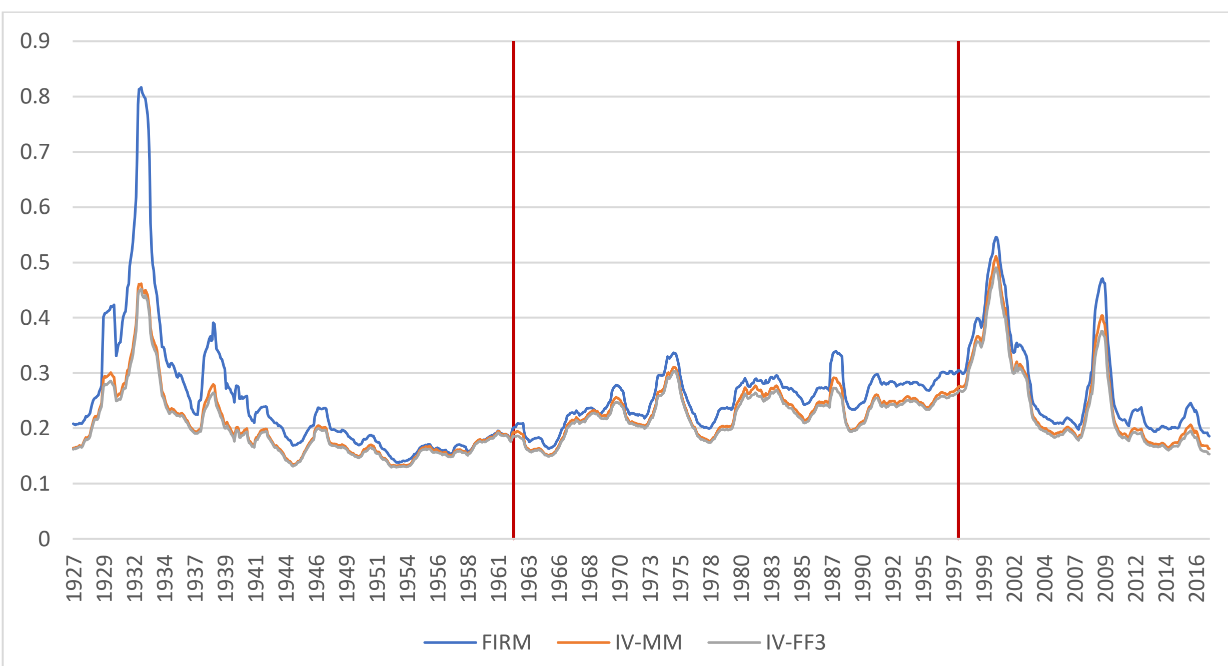
Figure 4: Idiosyncratic Volatility Series

Description: FIRM is CLMX's idiosyncratic volatility series estimated using Eq. (1). IV-MM is estimated monthly from the market model using daily returns. IV-FF3 is estimated monthly from the Fama and French (1993) three-factor model using daily returns. The sample period is July 1926 to December 2017. All series are value-weighted and reported as annualized standard deviations. Panel A plots the unadjusted mean of the monthly volatility series and Panel B plots the backward 12-month moving averages of the series. The area between the red vertical lines represents the CLMX period.

Interpretation: The three IV series are very closely related.



Panel A: IV Series

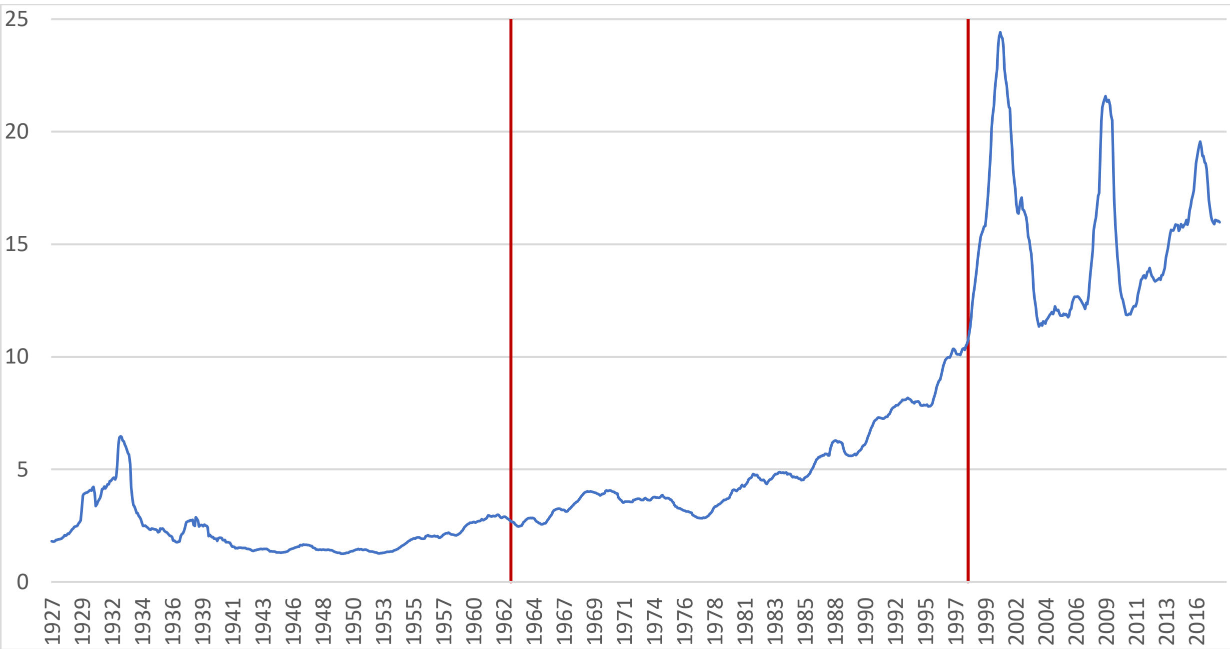


Panel B: IV Series, MA (12)

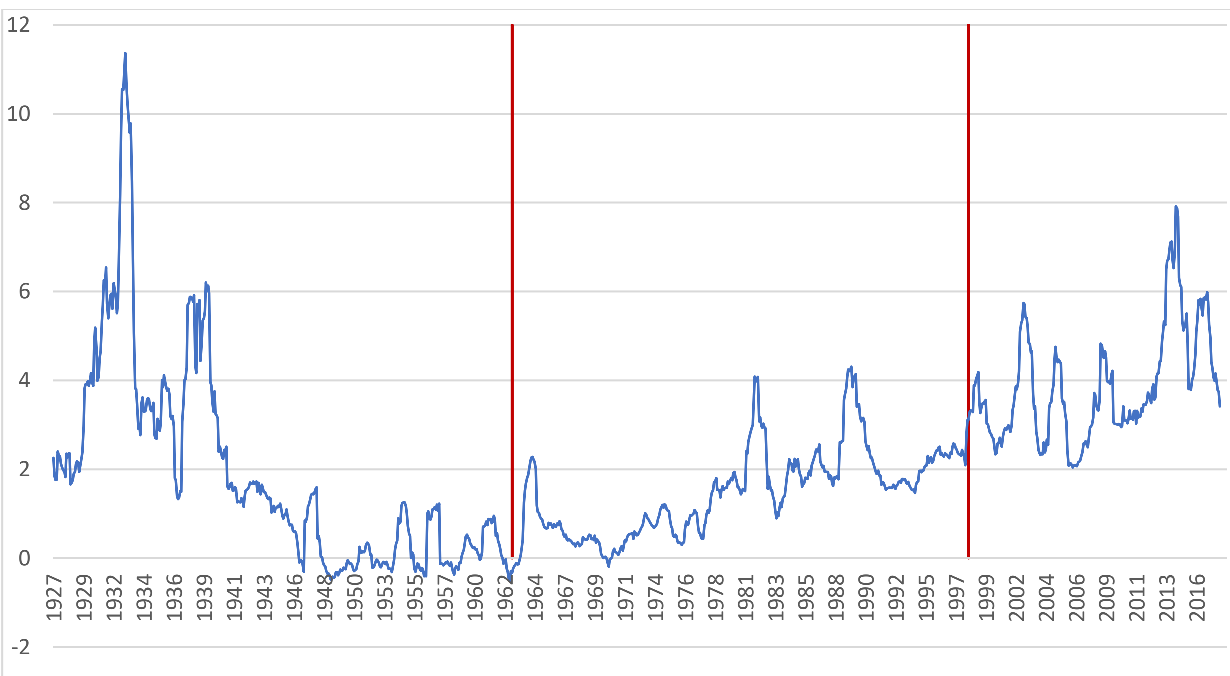
Figure 5: Cross-Sectional Moments of Idiosyncratic Volatility

Description: This figure plots the 12-month backward moving average of the cross-sectional moments of monthly idiosyncratic volatility. Panels A, B, and C report the value-weighted cross-sectional standard deviation, skewness, and kurtosis of monthly stock-level IV-FF3, respectively. IV-FF3 is the standard deviation of the residuals estimated monthly from the Fama-French three-factor model using daily returns. The sample period is June 1927 to December 2017. The area between the red vertical lines represents the CLMX period.

Interpretation: After the Great Depression, the cross-sectional moments of IV plotted in this figure exhibit an increasing trend.

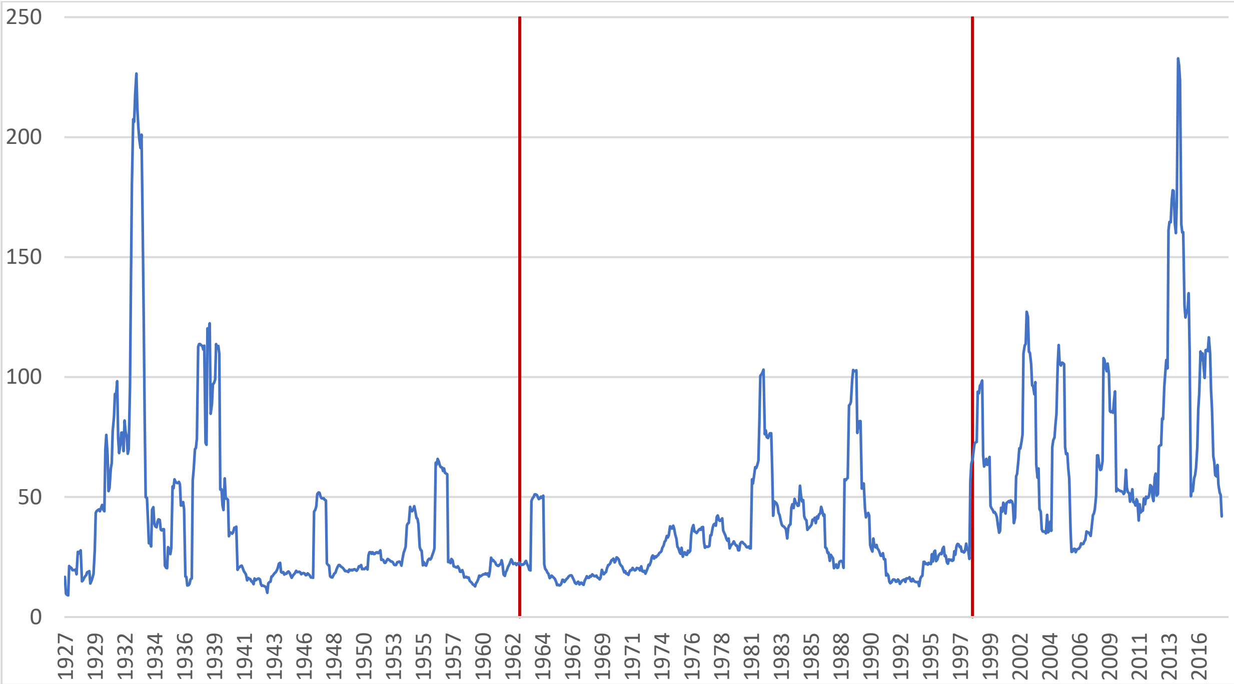


Panel A: Standard Deviation



Panel B: Skewness

Figure 5 (continued)

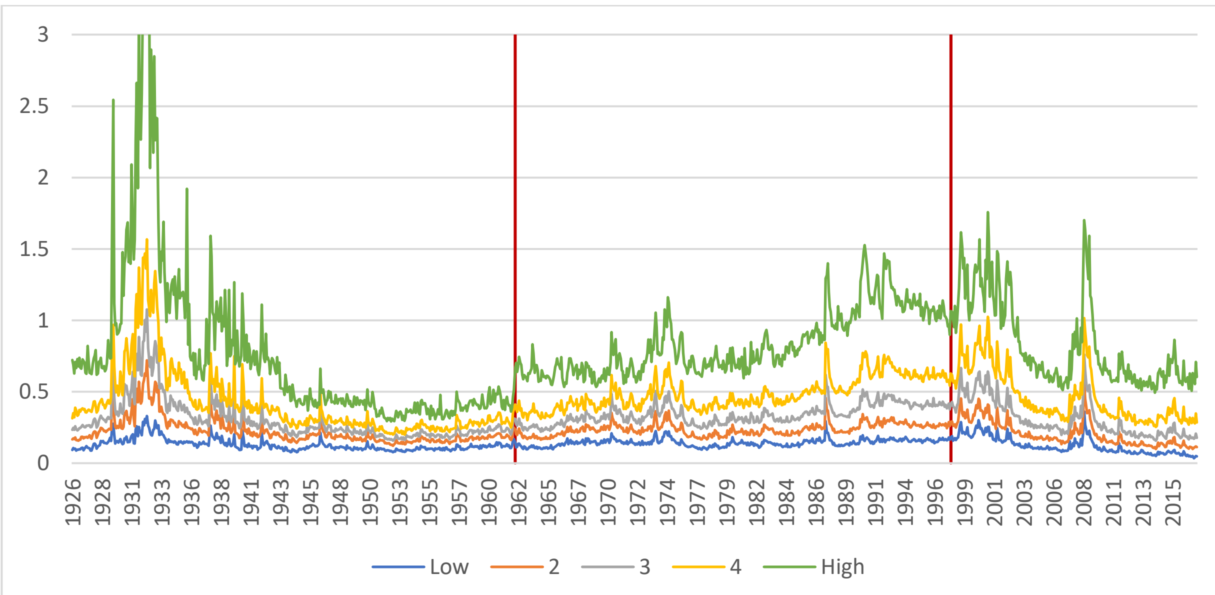


Panel C: Kurtosis

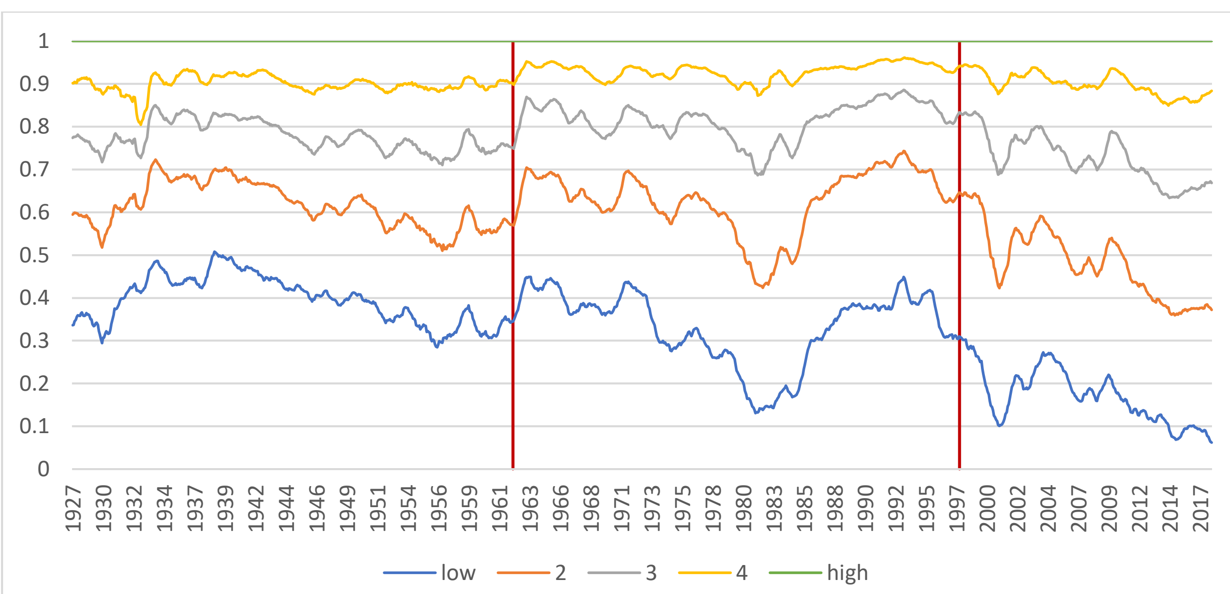
Figure 6: Idiosyncratic Volatility Quintiles

Description: Panel A plots the monthly level of IV-FF3 across IV-FF3–sorted quintiles. The series are value-weighted and reported as annualized standard deviations. Panel B plots the proportional contribution to the aggregate IV of the market from each IV-FF3 quintile. The contributions are calculated by multiplying each quintile-month IV by its market cap weight in the prior month and then transforming these values to proportions out of 1. The backward 12-month moving averages of these contributions are plotted. IV-FF3 is estimated monthly from the Fama-French three-factor model using daily returns. The sample period is July 1926 to December 2017. The area between the red vertical lines represents the CLMX period.

Interpretation: In Panel A, the spread in IV between the low and high quintile groups increases from the 1950s until the end of the CLMX sample period. This spread narrows in the post-CLMX period. In Panel B, it is the low-IV group whose contribution to aggregate IV has time-varied the most. In contrast, the high-IV group's contribution has been relatively stable at around 10%.



Panel A: IV-FF3 Levels in IV Quintiles



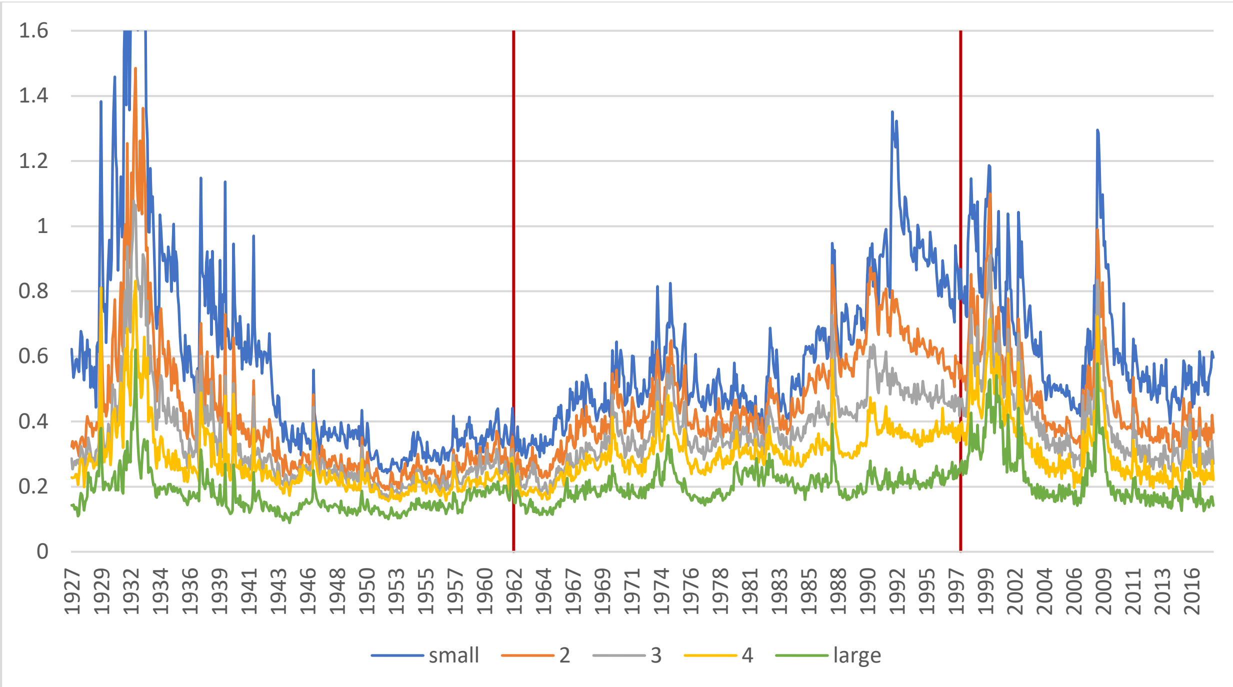
Panel B: Contribution to Aggregate IV by IV Quintiles

Figure 7: IV in Firm Characteristic Quintiles

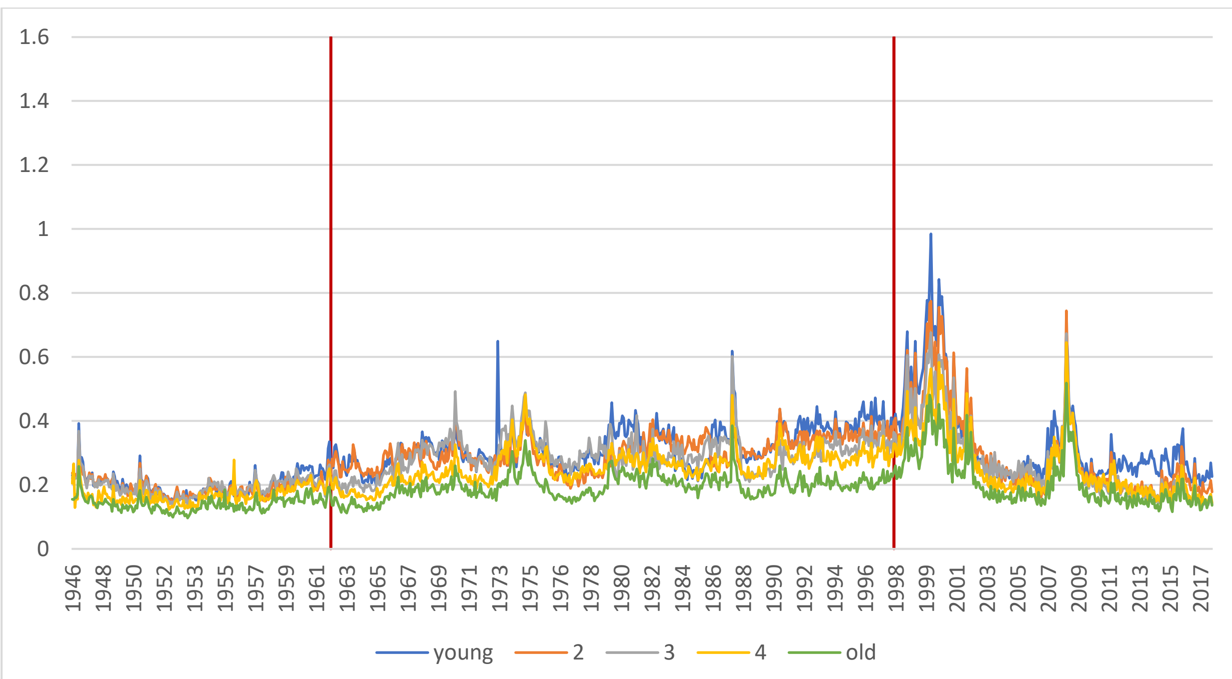
Description: This figure plots the monthly level of IV-FF3 across firm characteristic-sorted quintiles. The series are value-weighted and reported as annualized standard deviations. IV-FF3 is estimated monthly from the Fama-French (1993) three-factor model using daily returns. Panel A sorts by size (proxied by market capitalization), Panel B sorts by age (in years), Panel C sorts by illiquidity (calculated using the Amihud (2002) illiquidity ratio), Panel D sorts by institutional ownership, Panel E sorts by book-to-market (BM), and Panel F sorts by momentum. The sample period is July 1927 to December 2017 for size, illiquidity, BM, and momentum; April 1946 to December 2017 for age; and April 1980 to December 2017 for institutional ownership. The area between the red vertical lines represents the CLMX period.

Interpretation: The widest spread in IV between the low and high firm characteristic-sorted groups is for size and illiquidity. Age, institutional ownership, book-to-market, and to a lesser extent momentum have narrower spreads in IV between the low and high groups. Similar to the IV-sorted groups in Figure 6, the spread between low and high groups for size and illiquidity increases from the 1950s until the end of the CLMX sample period and then narrows in the post-CLMX period.

Figure 7 (continued)

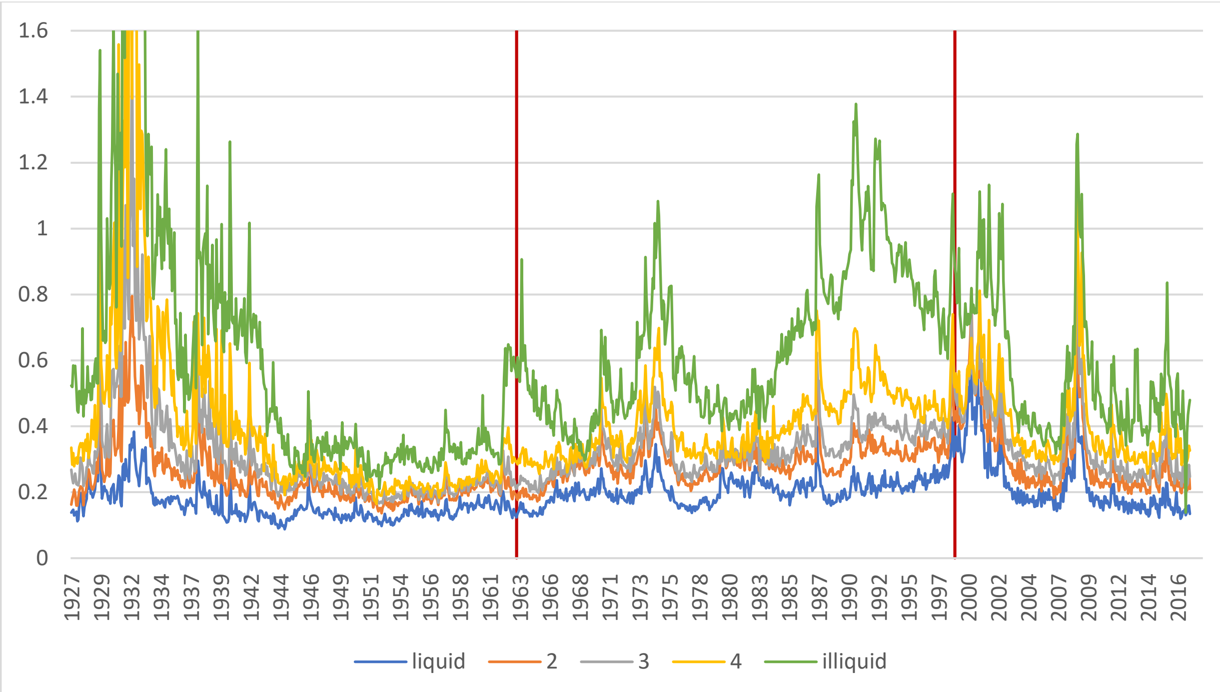


Panel A: IV in Size Quintiles

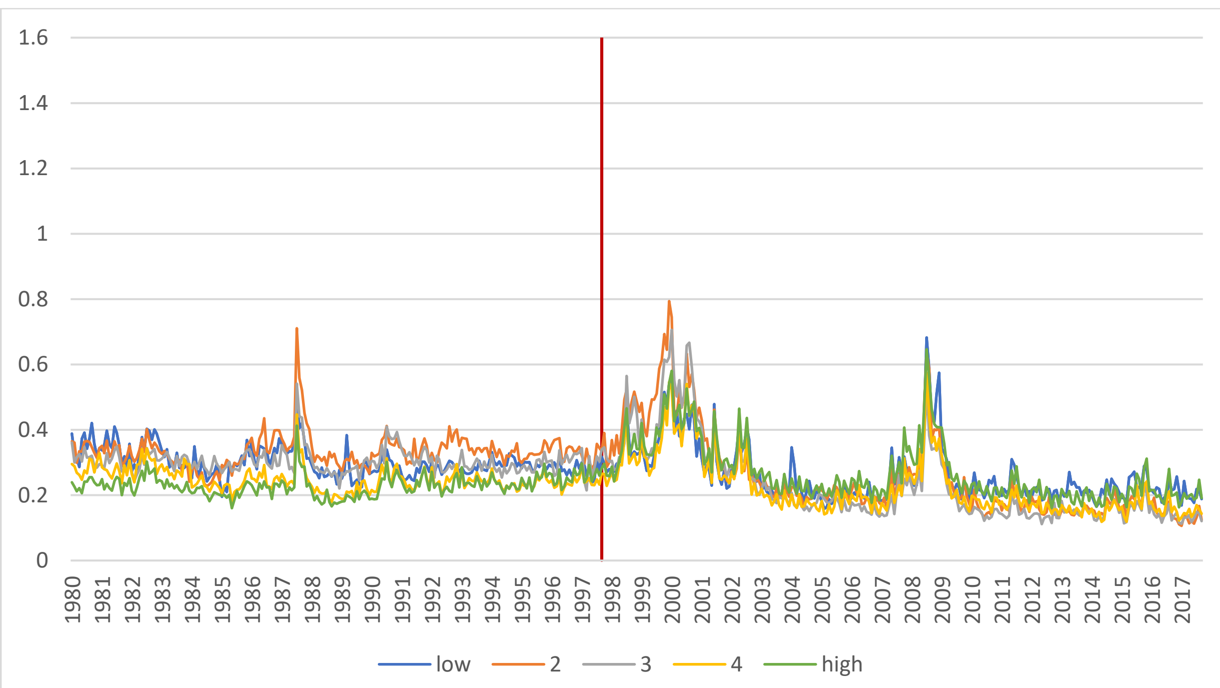


Panel B: IV in Age Quintiles

Figure 7 (continued)

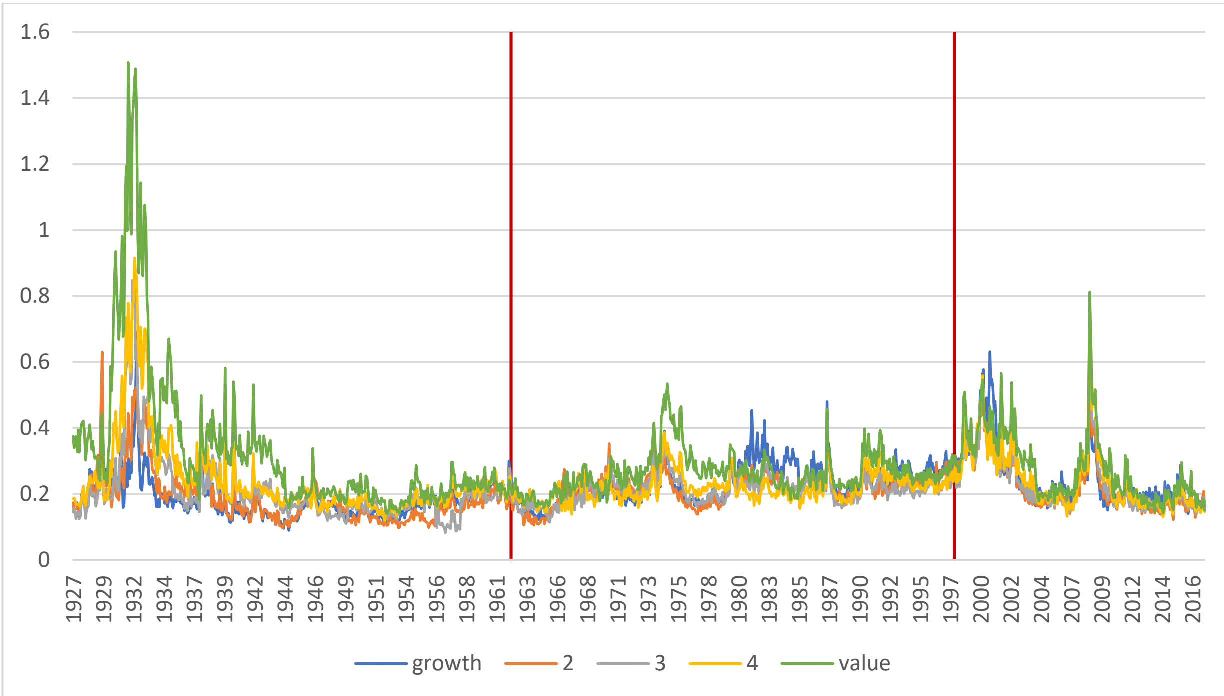


Panel C: IV in Illiquidity Quintiles

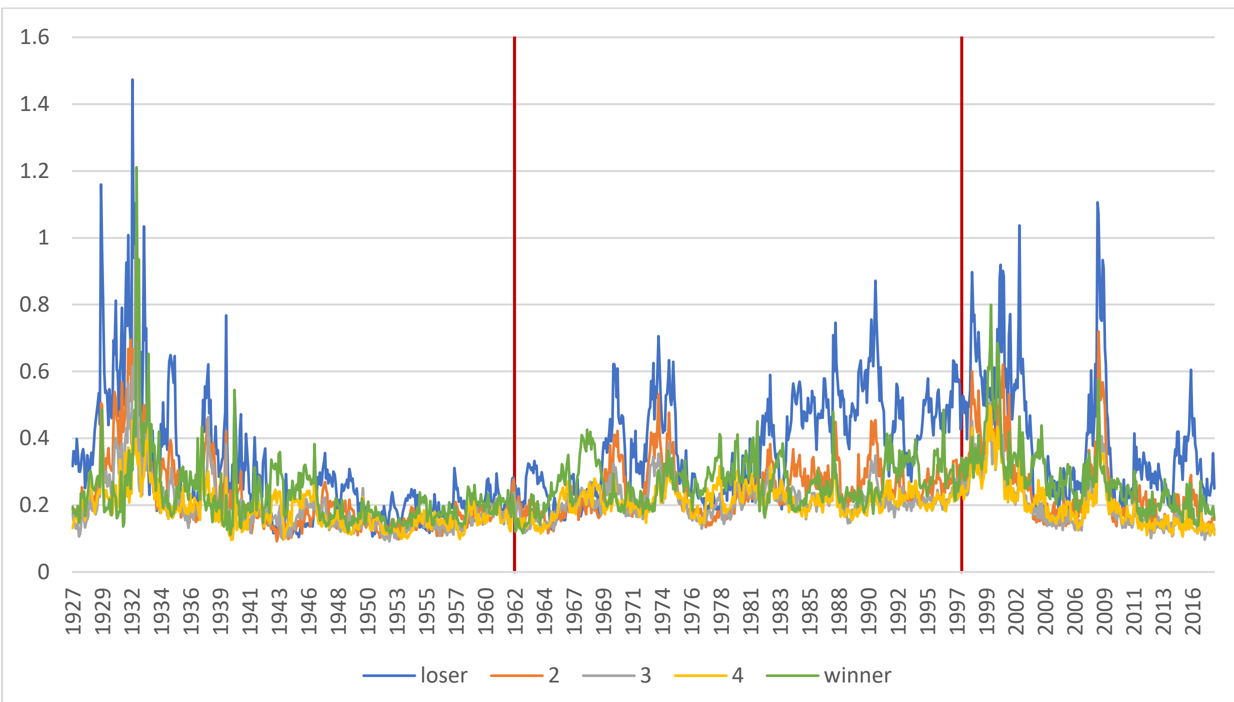


Panel D: IV in Institutional Ownership Quintiles

Figure 7 (continued)



Panel E: IV in BM Quintiles



Panel F: IV in Momentum Quintiles

Table 1: Unit Roots Tests: Replication

Description: This table replicates Table II in CLMX. It presents the augmented Dickey-Fuller unit root *ρ*-tests and *t*-tests for monthly volatility series constructed using daily data. Panel A displays our replication of CLMX's sample period from July 1962 to December 1997. Panel B, from CLMX's Table II, facilitates comparison. MKT, IND, and FIRM represent market-, industry-, and firm-level volatility (value-weighted variances) computed from Eqs. (1), (4), and (8). Unadjusted volatilities are labelled raw data. The volatilities labelled "down-weighted crash" replace the largest observations with the second-largest observation in the series. Regressions for unit root tests include a constant or a constant with a time trend. Following Campbell and Perron (1991), lag order is determined by the "general to specific method". *p*-values are reported in parentheses below the coefficient estimates.

Interpretation: The replicated results in Panel A are very similar to CLMX's results in Panel B. The hypothesis of a unit root is rejected for all three volatility series, indicating that all series are stationary.

	Raw Data			Down-Weighted Crash		
	MKT	IND	FIRM	MKT	IND	FIRM
Panel A: Replicated Results						
			Constant			
p-test	-237	-58	-42	-150	-57	-28
	(0.0001)	(0.0017)	(0.0017)	(<.0001)	(0.0017)	(0.0017)
t-test	-9.54	-4.69	-4.16	-8.61	-4.78	-3.47
	(<.0001)	(0.0002)	(0.0010)	(<.0001)	(0.0001)	(0.0097)
Lag order	2	5	5	1	4	5
			Constant and Trend			
p-test	-303	-95	-100	-152	-64	-48
	(0.0001)	(0.0007)	(0.0001)	(0.0001)	(0.0007)	(0.0007)
t-test	-12.25	-6.17	-6.64	-8.67	-5.03	-4.39
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.0002)	(0.0025)
Lag order	1	3	2	1	4	5
Panel B: Original Results						
			Constant			
p-test	-328	-103	-80.3	-175	-88.5	-46.5
t-test	-12.17	-4.59	-3.98	-8.55	-4.28	-3.29
Lag order	2	5	5	1	4	5
			Constant and Trend			
p-test	-330	-125	-145	-177	-91.7	-79.1
t-test	-12.24	-5.6	-6.35	-8.60	-4.36	-4.34
Lag order	1	3	2	1	4	5

Table 2: Descriptive Statistics and Linear Trends: Replication

Description: This table replicates Table III of CLMX and also reports the first order autocorrelations from Table I of CLMX. It provides descriptive statistics and linear trends for volatility series at the daily, weekly, and monthly levels. MKT, IND, and FIRM represent market-, industry-, and firm-level volatility computed from Eqs. (1), (4), and (8), respectively. Panel A displays our replication of CLMX's sample period from July 1962 to December 1997. Panel B, from CLMX's Table II, facilitates comparison. In each panel, we present volatilities constructed using daily, weekly, and monthly data. Large firms refer to the largest 2,039 stocks by market capitalization every month; 2,039 is the total number of firms in the first month of CLMX's sample in July 1962. All volatility series are value-weighted variances except for those in the bottom of the panel, which are equal-weighted (EW) variances. We annualize the monthly variances before multiplying them by 100. Linear trend coefficients from linear trend regressions for volatility measures, along with t_{PS}, the t-stat of the PS test (Vogelsang, 1998), are also reported.

Interpretation: The replicated results in Panel A are very similar to CLMX's results in Panel B. The mean of FIRM is considerably higher than that of MKT and IND. FIRM is also more persistent than MKT and IND, as is evidenced by higher first order autocorrelations. IND is less volatile than both MKT and FIRM.

	Raw Data			Down-Weighted Crash		
	MKT	IND	FIRM	MKT	IND	FIRM
Panel A: Replicated Results						
			Daily			
Mean * 10^2	1.464	0.950	6.734	1.338	0.941	6.680
Std. dev. * 10^2	3.346	0.615	2.873	1.401	0.540	2.398
Std. dev. * 10^2 detrended	3.338	0.601	2.569	1.395	0.526	2.049
Linear trend * 10^5	0.156	0.088	0.871	0.093	0.084	0.844
t_{PS}	(1.344)	(1.494)	(2.951)	(0.877)	(1.261)	(2.593)
1st order autocorrelation	0.143	0.472	0.555	0.476	0.602	0.745
			Weekly			
Mean * 10^2	1.669	1.118	6.157	1.653	1.116	6.151
Std. dev. * 10^2	2.383	0.707	2.234	2.225	0.694	2.200
Std. dev. * 10^2 detrended	2.383	0.089	2.011	2.225	0.681	1.971
Linear trend * 10^5	0.002	0.091	0.659	0.006	0.0881	0.661
t_{PS}	(0.444)	(1.216)	(1.602)	(0.388)	(1.185)	(1.633)
1st order autocorrelation	0.319	0.459	0.713	0.364	0.476	0.721
			Monthly			
Mean * 10^2	N/A	1.267	5.252	N/A	1.263	5.251
Std. dev. * 10^2	N/A	0.956	2.170	N/A	0.931	2.160
Std. dev. * 10^2 detrended	N/A	0.951	1.954	N/A	0.926	1.942
Linear trend * 10^5	N/A	0.067	0.639	N/A	0.067	0.639
t_{PS}	N/A	(0.862)	(1.822)	N/A	(0.862)	(1.822)
1st order autocorrelation	N/A	0.339	0.522	N/A	0.345	0.526
			Daily: Large Firms			
Mean * 10^2	1.513	1.006	5.816	1.381	0.997	5.771
Std. dev. * 10^2	3.462	0.650	2.434	1.435	0.575	2.006
Std. dev. * 10^2 detrended	3.451	0.628	2.362	1.425	0.552	1.928
Linear trend * 10^5	0.178	0.114	0.398	0.113	0.110	0.376
t_{PS}	(1.401)	(1.731)	(1.303)	(0.963)	(1.506)	(1.083)
1st order autocorrelation	0.145	0.489	0.501	0.145	0.267	0.442

			Daily: EW			
Mean * 10^2	0.971	1.293	36.799	0.922	1.284	36.719
Std. dev. * 10^2	2.202	0.834	24.564	1.490	0.764	24.182
Std. dev. * 10^2 detrended	2.198	0.785	16.147	1.481	0.714	15.676
Linear trend * 10^5	-0.086	0.190	12.530	-0.110	0.183	12.463
t_{PS}	(-0.576)	(0.599)	(0.863)	(-0.976)	(0.761)	(1.086)
1st order autocorrelation	0.126	0.730	0.925	0.244	0.745	0.930

	Raw Data			Down-Weighted Crash		
	MKT	IND	FIRM	MKT	IND	FIRM
Panel B: Original Results						
			Daily			
Mean * 10^2	1.542	1.032	6.436	1.409	1.027	6.383
Std. dev. * 10^2	3.500	0.663	2.912	1.469	0.623	2.446
Std. dev. * 10^2 detrended	3.488	0.663	2.536	1.463	0.619	2.013
Linear trend * 10^5	0.156	0.062	0.965	0.090	0.060	0.939
PS-statistic	0.261	0.086	1.005	0.144	0.082	0.958
1st order autocorrelation	0.149	0.529	0.591	0.494	0.591	0.776
			Weekly			
Mean * 10^2	1.897	1.218	5.842	1.858	1.218	5.842
Std. dev. * 10^2	2.522	0.727	2.210	2.158	0.727	2.210
Std. dev. * 10^2 detrended	2.522	0.724	1.923	2.158	0.721	1.919
Linear trend * 10^5	0.003	0.053	0.737	-0.017	0.053	0.737
PS-statistic	0.116	0.096	0.410	0.082	0.096	0.410
			Monthly			
Mean * 10^2	N/A	1.269	5.039	N/A	1.269	5.039
Std. dev. * 10^2	N/A	1.032	2.203	N/A	1.032	2.203
Std. dev. * 10^2 detrended	N/A	1.032	1.930	N/A	1.032	1.929
Linear trend * 10^5	N/A	0.026	0.720	N/A	0.026	0.720
PS-statistic	N/A	0.094	0.780	N/A	0.093	0.780
			Daily: Large firms			
Mean * 10^2	1.599	1.090	5.877	1.145	1.086	5.828
Std. dev. * 10^2	3.675	0.744	2.671	1.507	0.675	2.210
Std. dev. * 10^2 detrended	3.464	0.693	2.557	1.498	0.658	2.080
Linear trend * 10^5	0.185	0.087	0.524	0.116	0.085	0.499
PS-statistic	0.296	0.111	0.590	0.172	0.107	0.055
			Daily: EW			
Mean * 10^2	1.211	1.251	33.903	1.149	1.251	33.903
Std. dev. * 10^2	2.619	0.554	23.112	1.718	0.412	23.112
Std. dev. * 10^2 detrended	2.612	0.554	14.116	1.704	0.554	14.116
Linear trend * 10^5	-0.114	0.022	12.386	-0.145	0.022	12.386
PS-statistic	-0.076	-0.004	11.231	-0.132	-0.004	11.219

Table 3: Correlations between CLMX Volatility Measures: Replication

Description: This table replicates Table V in CLMX. Correlations among monthly volatility measures are reported. The left (right) panel presents correlations between the unadjusted (detrended) volatility series. MKT, IND, and FIRM represent market-, industry-, and firm-level volatility (value-weighted variances) computed from Eqs. (1), (4), and (8) using daily data, respectively. Panel A displays our replication of CLMX's sample period from July 1962 to December 1997. Panel B, from CLMX's Table II, facilitates comparison.

Interpretation: The replicated results in Panel A are very similar to CLMX's results in Panel B. All three volatility series are highly correlated with each other.

	With Trend			Detrended		
	MKT	IND	FIRM	MKT	IND	FIRM
Panel A: Replicated Results						
MKT	1	0.700	0.714	1	0.699	0.780
IND		1	0.847		1	0.875
FIRM			1			1
Panel B: Original Results						
MKT	1	0.645	0.708	1	0.641	0.800
IND		1	0.705		1	0.767
FIRM			1			1

Table 4: Mean and Variance Decomposition: Replication

Description: Replicating Table VI in CLMX, this table decomposes the mean and variance of the volatility series. MKT, IND, and FIRM represent market-, industry-, and firm-level volatility (value-weighted variances) computed from Eqs. (1), (4), and (8), respectively. The reported values are the proportions of MKT, IND, and FIRM in the total mean and variance of the volatility of a typical stock. The left panel displays our replication of CLMX's sample period from July 1962 to December 1997. The right panel reports CLMX's results to facilitate comparison.

Interpretation: The replicated results in the left panel are very similar to CLMX's results in the right panel. FIRM is the largest component of the volatility of a typical stock with a mean proportion exceeding 70%. FIRM variance and the covariation between MKT and FIRM account for more than 60% of the total time-series variation in volatility.

July 1962 to December 1997						
	Replicated Results			Original Results		
	MKT	IND	FIRM	MKT	IND	FIRM
Mean						
7/62 – 12/97	0.149	0.105	0.746	0.160	0.116	0.724
7/62 – 6/71	0.143	0.112	0.745	0.162	0.126	0.712
1/88 – 12/97	0.127	0.100	0.773	0.134	0.097	0.769
Variance						
	Raw Series					
MKT	0.141	0.074	0.323	0.149	0.081	0.328
IND		0.020	0.137		0.027	0.133
FIRM			0.304			0.282
	Conditional Means					
MKT	0.044	0.056	0.267	0.099	0.067	0.334
IND		0.025	0.187		0.026	0.137
FIRM			0.422			0.337

Table 5: Cyclical Behavior: GDP Growth: Replication

Description: This table replicates Table IX in CLMX and considers whether the volatility measures can predict GDP growth in the next quarter. The OLS regression outputs with GDP growth (GDP_t) as the dependent variable are reported. MKT, IND, and FIRM represent market-, industry-, and firm-level volatility (value-weighted variances) computed from Eqs. (1), (4), and (8). They are linearly detrended and time-aggregated to a quarterly frequency. RVW denotes the quarterly return on the CRSP value-weighted portfolio. Coefficients are reported with heteroskedasticity consistent *t*-statistics in parentheses using the technique outlined in Newey and West (1987). The sample period is quarter 4 1962 to quarter 4 1997.

Interpretation: The replicated results in Panel A are very similar to CLMX's results in Panel B. Each individual volatility measure is negatively significant when it is the only volatility measure in the regression. This indicates that all of the volatility series can predict GDP growth in the next quarter. When regressed together, the volatility series lose their significance in all but one regression specification.

GDP_{t-1}	RVW_{t-1}	MKT_{t-1}	IND_{t-1}	$FIRM_{t-1}$	R^2
Panel A: Replicated Results					
0.292	0.088				0.106
(3.15)	(2.48)				
0.217	0.052	-3.415			0.147
(2.26)	(1.27)	(-2.39)			
0.195	0.065		-8.410		0.158
(1.94)	(1.69)		(-2.42)		
0.198	0.065			-2.353	0.172
(2.01)	(1.71)			(-2.98)	
0.190	0.056	-1.415	-6.181		0.156
(1.88)	(1.42)	(-0.92)	(-1.49)		
0.198	0.066	0.043		-2.373	0.166
(2.00)	(1.73)	(0.02)		(-2.06)	
0.195	0.065		-0.927	-2.148	0.166
(1.97)	(1.67)		(-0.15)	(-1.58)	
0.195	0.065	0.043	-0.927	-2.167	0.160
(1.95)	(1.68)	(0.02)	(-0.15)	(-1.29)	
Panel B: Original Results					
0.330	0.020				0.143
(4.20)	(2.55)				
0.251	0.012	-0.701			0.190
(2.95)	(1.37)	(-2.38)			
0.211	0.015		-1.841		0.213
(2.27)	(1.76)		(-2.43)		
0.238	0.014			-0.477	0.206
(2.54)	(1.58)			(-3.00)	
0.199	0.013	-0.314	-1.470		0.219
(2.31)	(1.42)	(-0.88)	(-1.63)		
0.236	0.013	-0.073		-0.441	0.206
(2.56)	(1.66)	(-0.18)		(-1.71)	
0.201	0.013		-1.239	-0.250	0.222
(2.34)	(1.48)		(-1.18)	(-1.00)	
0.200	0.013	-0.058	-1.237	-0.222	0.222
(2.14)	(1.53)	(-0.14)	(-1.25)	(-0.74)	

Table 6: Unit Root Tests: Out-of-Sample

Description: This table replicates Table II in CLMX. It presents the augmented Dickey-Fuller unit root ρ-tests and t-tests for monthly volatility series constructed using daily data. Panel A performs the analysis in the pre-CLMX July 1926 to June 1962 period. Panel B performs the analysis in the post-CLMX January 1998 to December 2017 period. MKT, IND, and FIRM represent market-, industry-, and firm-level volatility (value-weighted variances) computed from Eqs. (1), (4), and (8). Unadjusted volatilities are labelled raw data. The volatilities labelled "Down-weighted crash" replace the largest observations with the second-largest observation in the series. Regressions for unit root tests include a constant or a constant with a time trend. Following Campbell and Perron (1991), lag order is determined by the "general to specific method". p-values are reported in parentheses below the coefficient estimates.

Interpretation: The out-of-sample results in this table are similar to the CLMX period results in Table 2. The hypothesis of a unit root is rejected in all instances in Panel A and in the majority of instances in Panel B. This indicates that the three volatility series are stationary.

	Raw Data			Down-Weighted Crash		
	MKT	IND	FIRM	MKT	IND	FIRM
Panel A: July 1926 to June 1962						
			Constant			
p-test	-98	-89	-42	-138	-65	-35
	(0.0017)	(0.0017)	(0.0017)	(0.0001)	(0.0017)	(0.0017)
t-test	-6.59	-5.55	-4.14	-8.26	-5.12	-3.83
	(<.0001)	(<.0001)	(0.0010)	(<.0001)	(<.0001)	(0.0030)
Lag order	2	5	5	1	4	5
			Constant and Trend			
p-test	-194	-153	-86	-172	-86	-48
	(0.0001)	(0.0001)	(0.0007)	(0.0001)	(0.0007)	(0.0007)
t-test	-9.78	-7.46	-6.24	-9.21	-5.73	-4.42
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.0023)
Lag order	1	3	2	1	4	5
Panel B: January 1998 to December 2017						
			Constant			
p-test	-73	-13	-13	-73	-26	-12
	(0.0015)	(0.0553)	(0.0669)	(0.0015)	(0.0024)	(0.0844)
t-test	-5.58	-2.40	-2.33	-5.99	-3.28	-2.25
	(<.0001)	(0.1426)	(0.1646)	(<.0001)	(0.0174)	(0.1908)
Lag order	2	5	5	1	4	5
			Constant and Trend			
p-test	-94	-43	-28	-74	-38	-21
	(0.0006)	(0.0006)	(0.0105)	(0.0006)	(0.0011)	(0.0537)
t-test	-6.82	-4.25	-3.66	-6.06	-3.92	-2.99
	(<.0001)	(0.0045)	(0.0269)	(<.0001)	(0.0129)	(0.1376)
Lag order	1	3	2	1	4	5

Table 7: Descriptive Statistics and Linear Trends: Out-of-Sample

Description: This table replicates Table III of CLMX and also reports the first order autocorrelations from Table I of CLMX. It provides descriptive statistics and linear trends for volatility series at the daily, weekly, and monthly levels. MKT, IND, and FIRM represent market-, industry-, and firm-level volatility computed from Eqs. (1), (4), and (8), respectively. Panel A displays the results in the pre-CLMX period from July 1926 to June 1962. Panel B performs the analysis in the post-CLMX January 1998 to December 2017 period. In each panel, we present volatilities constructed using daily, weekly, and monthly data. Large firms refer to the largest 2,039 stocks by market capitalization every month; 2,039 is the total number of firms in the first month of CLMX's sample in July 1962. All volatility series are value-weighted variances except for those in the bottom panel, which are equal-weighted (EW) variances. We annualize the monthly variances before multiplying them by 100. Linear trend coefficients from linear trend regressions for volatility measures, along with t_{PS}, the t-stat of the PS test (Vogelsang, 1998), are also reported.

Interpretation: In contrast to the CLMX period in Table 2, where the linear trend coefficients were almost always positive, they are always negative in this table, significantly in Panel A and insignificantly in Panel B. This indicates that the three volatility series have downward trends in the periods before and after the CLMX sample.

	Raw Data			Down-Weighted Crash		
	MKT	IND	FIRM	MKT	IND	FIRM
Panel A: July 1926 to June 1962						
			Daily			
Mean * 10^2	3.716	1.957	7.935	3.648	1.859	7.804
Std. dev. * 10^2	7.253	4.965	14.086	6.721	3.579	12.649
Std. dev. * 10^2 detrended	6.771	4.785	13.129	6.237	3.366	11.639
Linear trend * 10^5	-1.737	-0.886	-3.406	-1.673	-0.812	-3.306
t_{PS}	(-2.370)	(-1.940)	(-1.750)	(-2.046)	(-2.125)	(-1.934)
1st order autocorrelation	0.626	0.689	0.824	0.672	0.821	0.863
			Weekly			
Mean * 10^2	3.951	1.640	4.812	3.925	1.623	4.810
Std. dev. * 10^2	7.650	2.522	5.218	7.455	2.333	5.210
Std. dev. * 10^2 detrended	7.128	2.342	4.673	6.930	2.146	4.665
Linear trend * 10^5	-1.854	-0.625	-1.549	-1.834	-0.612	-1.548
t_{PS}	(-1.932)	(-2.117)	(-1.802)	(-1.925)	(-2.074)	(-1.801)
1st order autocorrelation	0.680	0.754	0.573	0.679	0.773	0.853
			Monthly			
Mean * 10^2	N/A	1.693	3.792	N/A	1.678	3.748
Std. dev. * 10^2	N/A	3.016	4.917	N/A	2.855	4.468
Std. dev. * 10^2 detrended	N/A	2.885	4.599	N/A	2.721	4.136
Linear trend * 10^5	N/A	-0.586	-1.162	N/A	-0.576	-1.129
t_{PS}	N/A	(-2.129)	(-2.446)	N/A	(-2.085)	(-2.450)
1st order autocorrelation	N/A	0.393	0.622	N/A	0.415	0.663
			Daily: Large firms			
Mean * 10^2	3.717	2.001	7.172	3.650	1.901	7.041
Std. dev. * 10^2	7.269	5.058	13.362	6.741	3.637	11.869
Std. dev. *10^2 detrended	6.785	4.883	12.492	6.256	3.431	10.945
Linear trend * 10^5	-1.740	-0.881	-3.165	-1.676	-0.805	-3.065
t_{PS}	(-2.032)	(-2.186)	(-2.156)	(-1.956)	(-2.027)	(-2.100)
1st order autocorrelation	0.628	0.687	0.821	0.674	0.820	0.864

			Daily: EW			
Mean * 10^2	4.266	6.954	32.525	4.249	6.929	32.024
Std. dev. * 10^2	8.521	11.117	53.364	8.386	10.954	49.203
Std. dev. * 10^2 detrended	8.050	9.653	47.589	7.911	9.480	43.180
Linear trend * 10^5	-1.865	-3.681	-16.117	-1.856	-3.662	-15.745
t_{PS}	(-2.371)	(-1.938)	(-1.749)	(-2.375)	(-1.921)	(-1.604)
1st order autocorrelation	0.484	0.775	0.780	0.490	0.788	0.860

	Raw Data			Down-Weighted Crash		
	MKT	IND	FIRM	MKT	IND	FIRM
Panel B: January 1998 to December 2017						
			Daily			
Mean * 10^2	3.686	2.244	8.856	3.588	2.242	8.838
Std. dev. * 10^2	6.635	2.647	8.083	5.756	2.635	7.992
Std. dev. * 10^2 detrended	6.600	2.403	6.957	5.714	2.390	6.849
Linear trend * 10^5	-0.812	-1.332	-4.939	-0.828	-1.333	-4.942
t_{PS}	(-0.055)	(-1.383)	(-1.443)	(-0.109)	(-1.378)	(-1.414)
1st order autocorrelation	0.705	0.807	0.859	0.736	0.809	0.864
			Weekly			
Mean * 10^2	3.143	2.196	8.308	3.027	2.185	8.291
Std. dev. * 10^2	6.479	2.478	7.229	5.383	2.426	7.147
Std. dev. * 10^2 detrended	6.440	2.216	6.210	5.333	2.165	6.113
Linear trend * 10^5	-0.860	-1.330	-4.441	-0.879	-1.313	-4.443
t_{PS}	(-0.283)	(-1.500)	(-1.405)	(-0.409)	(-1.465)	(-1.376)
1st order autocorrelation	0.404	0.788	0.859	0.411	0.798	0.862
			Monthly			
Mean * 10^2	N/A	2.045	7.614	N/A	2.036	7.559
Std. dev. * 10^2	N/A	2.457	6.720	N/A	2.399	6.364
Std. dev. * 10^2 detrended	N/A	2.190	5.726	N/A	2.131	5.352
Linear trend * 10^5	N/A	-1.337	-4.223	N/A	-1.321	-4.133
t_{PS}	N/A	(-0.692)	(-1.388)	N/A	(-1.381)	(-1.297)
1st order autocorrelation	N/A	0.523	0.747	N/A	0.540	0.776
			Daily: Large firms			
Mean * 10^2	3.729	2.381	7.673	3.630	2.378	7.659
Std. dev. * 10^2	6.696	2.813	7.355	5.795	2.798	7.288
Std. dev. *10^2 detrended	6.656	2.542	6.354	5.747	2.526	6.274
Linear trend * 10^5	-0.877	-1.444	-4.448	-0.894	-1.444	-4.450
t_{PS}	(-1.102)	(-1.401)	(-1.396)	(-0.161)	(-1.395)	(-1.371)
1st order autocorrelation	0.704	0.809	0.856	0.735	0.811	0.861
			Daily: EW			
Mean * 10^2	2.623	2.165	42.836	2.565	2.154	42.442
Std. dev. * 10^2	4.918	1.642	35.047	4.434	1.570	32.877
Std. dev. * 10^2 detrended	4.918	1.633	30.497	4.434	1.560	27.926
Linear trend * 10^5	-0.031	-0.209	-20.728	-0.041	-0.210	-20.827
t_{PS}	(-0.444)	(-0.383)	(-1.937)	(-0.432)	(-0.405)	(-1.886)
1st order autocorrelation	0.680	0.743	0.670	0.700	0.747	0.737

Table 8: Correlations between CLMX Volatility Measures: Out-of-Sample

Description: This table replicates Table V in CLMX. Correlations among monthly volatility measures are reported. The left (right) panel presents correlations between the unadjusted (detrended) volatility series. MKT, IND, and FIRM represent market-, industry-, and firm-level volatility (value-weighted variances) computed from Eqs. (1), (4), and (8), respectively, using daily data. Panel A displays the results in the pre-CLMX July 1926 to June 1962 period. Panel B performs the analysis in the post-CLMX January 1998 to December 2017 period.

Interpretation: All three volatility series are highly correlated with each other and these correlations are similar to the CLMX period correlations in Table 3.

	With Trend			Detrended		
	MKT	IND	FIRM	MKT	IND	FIRM
Panel A: July 1926 to June 1962						
MKT	1	0.685	0.747	1	0.639	0.704
IND		1	0.939		1	0.931
FIRM			1			1
Panel B: January 1998 to December 2017						
MKT	1	0.675	0.662	1	0.693	0.706
IND		1	0.944		1	0.936
FIRM			1			1

Table 9: Mean and Variance Decomposition: Out-of-Sample

Description: Replicating Table VI in CLMX, this table decomposes the mean and variance of the volatility series. MKT, IND, and FIRM represent market-, industry-, and firm-level volatility (value-weighted variances) computed from Eqs. (1), (4), and (8), respectively. The reported values are the proportions of MKT, IND, and FIRM in the total mean and variance of the volatility of a typical stock. Panel A displays the results in the pre-CLMX July 1926 to June 1962 period. Panel B performs the analysis in the post-CLMX January 1998 to December 2017 period.

Interpretation: FIRM's contribution to the total volatility of a typical stock is around 60%, which is lower than in the CLMX period in Table 4, where it was around 75%. This decline is offset by an increase in MKT's contribution to around 25%. FIRM variance and the covariance between MKT and FIRM again account for around 60% of the total time-series variation in volatility.

July 1926 to June 1962			
	MKT	IND	FIRM
Mean			
7/26 – 6/62	0.274	0.140	0.586
7/26 – 12/35	0.274	0.142	0.584
1/35 – 6/62	0.228	0.152	0.621
Variance			
		Raw Series	
MKT	0.100	0.069	0.264
IND		0.029	0.188
FIRM			0.349
		Conditional Means	
MKT	0.067	0.079	0.292
IND		0.027	0.191
FIRM			0.344

January 1998 to December 2017			
	MKT	IND	FIRM
Mean			
1/98 – 12/17	0.245	0.153	0.603
Variance			
		Raw Series	
MKT	0.172	0.100	0.291
IND		0.030	0.161
FIRM			0.247
		Conditional Means	
MKT	0.087	0.080	0.162
IND		0.047	0.258
FIRM			0.366

Table 10: Cyclical Behavior: GDP Growth: Out-of-Sample

Description: This table replicates Table IX in CLMX and considers whether the volatility measures can predict GDP growth in the next quarter. The OLS regression outputs with GDP growth (GDP_t) as the dependent variable are reported. MKT, IND, and FIRM represent market-, industry-, and firm-level volatility (value-weighted variances) computed from Eqs. (1), (4), and (8). They are linearly detrended and time-aggregated to a quarterly frequency. RVW denotes the quarterly return on the CRSP value-weighted portfolio. Coefficients are reported with heteroskedasticity consistent *t*-statistics in parentheses using the technique outlined in Newey and West (1987). Panel A displays the results in the pre-CLMX period from quarter 3 1946 to quarter 3 1962. Panel B performs the analysis in the post-CLMX period from quarter 1 1998 to quarter 4 2017.

Interpretation: In the pre-CLMX period in Panel A, none of the volatility series can predict GDP growth in the next quarter. This contrasts with the CLMX period in Table 5 and the post-CLMX period in Panel B, where each individual volatility series is negatively significant when it is the only volatility measure in the regression.

GDP_{t-1}	RVW_{t-1}	MKT_{t-1}	IND_{t-1}	$FIRM_{t-1}$	R^2
Panel A: 1946 Q3 to 1962 Q3					
0.375	0.237				0.235
(3.56)	(2.28)				
0.378	0.213	-0.928			0.224
(3.63)	(2.09)	(-0.45)			
0.376	0.233		-1.091		0.222
(3.60)	(2.28)		(-0.25)		
0.375	0.236			-0.064	0.221
(3.57)	(2.32)			(-0.06)	
0.379	0.175	-3.123	5.844		0.214
(3.64)	(1.42)	(-0.56)	(0.49)		
0.381	0.170	-3.659		1.967	0.219
(3.64)	(1.57)	(-0.82)		(0.82)	
0.383	0.243		-22.441	5.660	0.220
(3.61)	(2.38)		(-1.20)	(1.19)	
0.384	0.200	-2.268	-14.839	4.979	0.209
(3.64)	(1.50)	(-0.40)	(-0.57)	(0.99)	
Panel B: 1998 Q1 to 2017 Q4					
0.038	-0.934				0.146
(1.05)	(-2.12)				
0.214	0.001	-0.934			0.196
(1.84)	(0.02)	(-2.12)			
0.183	0.007		-1.803		0.243
(2.45)	(0.24)		(-2.75)		
0.248	0.025			-0.432	0.188
(2.63)	(0.75)			(-1.71)	
0.167	0.000	-0.287	-1.550		0.237
(2.12)	(0.01)	(-0.57)	(-1.85)		
0.204	0.005	-0.638		-0.239	0.195
(2.02)	(0.17)	(-1.02)		(-0.69)	
0.155	-0.007		-4.469	0.979	0.272
(1.94)	(-0.24)		(-2.17)	(1.41)	
0.128	-0.020	-0.460	-4.290	1.061	0.272
(1.60)	(-0.59)	(-0.82)	(-2.23)	(1.61)	

Table 11: Correlations between CLMX Volatility Measures and Factor Model IVs

Description: This table reports correlations among monthly volatility measures over the period from July 1963 to December 2017. MKT, IND, and FIRM represent market-, industry-, and firm-level volatility computed from Eqs. (1), (4), and (8) using daily data. IV-MM, IV-FF3, IV-FF5, and IV-FF6 represent IV estimated using the market model, the Fama and French (1993) three-factor model, and the Fama and French (2015) five- and six-factor (five factors augmented with the momentum factor) models, respectively. The correlations are calculated from value-weighted variance series.

Interpretation: The correlations between all idiosyncratic volatility series (including FIRM) are extremely high.

	MKT	IND	FIRM	IV-MM	IV-FF3	IV-FF5	IV-FF6
MKT	1	0.662	0.689	0.651	0.585	0.573	0.563
IND		1	0.919	0.925	0.912	0.898	0.893
FIRM			1	0.990	0.979	0.977	0.973
IV-MM				1	0.991	0.989	0.986
IV-FF3					1	0.998	0.997
IV-FF5						1	0.999
IV-FF6							1

Table 12: Volatility across Subperiods

Description: This table reports the levels of monthly volatility measures over subperiods spanning July 1926 to December 2017. MKT, IND, and FIRM represent market-, industry-, and firm-level volatility computed from Eqs. (1), (4), and (8) using daily data. IV-MM and IV-FF3 represent IV estimated using the market model and the Fama and French (1993) three-factor model, respectively. All volatility series are value-weighted and are reported as annualized standard deviations.

Interpretation: Idiosyncratic volatility increases in each subperiod from the 1950s to the 1990s. It then falls in the last two subperiods.

Time period	MKT	IND	FIRM	IV-MM	IV-FF3
1926–2017	0.137	0.112	0.256	0.223	0.217
1926–1930	0.164	0.137	0.278	0.224	0.217
1931–1940	0.256	0.183	0.370	0.267	0.259
1941–1950	0.115	0.088	0.199	0.169	0.165
1951–1960	0.089	0.079	0.163	0.157	0.154
1961–1970	0.087	0.084	0.211	0.199	0.195
1971–1980	0.113	0.093	0.251	0.229	0.223
1981–1990	0.125	0.097	0.272	0.244	0.237
1991–2000	0.126	0.133	0.329	0.298	0.291
2001–2010	0.181	0.142	0.279	0.253	0.244
2011–2017	0.125	0.094	0.209	0.181	0.174

Table 13: IV in Quintile Groups across Subperiods

Description: This table reports the monthly level of IV-FF3 across IV-FF3–sorted quintiles over subperiods spanning July 1926 to December 2017. IV-FF3 is estimated monthly from the Fama-French three-factor model using daily returns. The series are value-weighted and are reported as annualized standard deviations.

Interpretation: IV increases in each quintile group from the 1950s to the 1990s and then falls in the last two subperiods. It increases much more markedly in high-IV stocks, compared to low-IV stocks, and then declines more markedly in low-IV stocks, compared with high-IV stocks.

Time period	Low	2	3	4	High
1926–2017	0.133	0.225	0.318	0.454	0.810
1926–1930	0.134	0.229	0.321	0.460	0.856
1931–1940	0.169	0.319	0.455	0.664	1.424
1941–1950	0.113	0.190	0.243	0.316	0.518
1951–1960	0.102	0.160	0.200	0.253	0.376
1961–1970	0.133	0.215	0.286	0.384	0.616
1971–1980	0.139	0.227	0.321	0.449	0.736
1981–1990	0.142	0.235	0.345	0.500	0.893
1991–2000	0.178	0.295	0.449	0.669	1.174
2001–2010	0.133	0.220	0.328	0.486	0.865
2011–2017	0.071	0.132	0.204	0.319	0.608

Table 14: Firm Characteristics in IV Quintiles

Description: This table reports summary statistics for IV quintiles over the period from April 1980 to December 2017. Firm characteristics include size (market capitalization in millions of dollars), age (in years), the Amihud (2002) illiquidity ratio (multiplied by one million), institutional ownership, book-to-market ratio, and momentum over the last 12 months. All variables are winsorized at the 1st and 99th percentile. Each month, stocks are sorted into quintiles based on IV-FF3 estimated using the Fama and French (1993) three-factor model. The reported means of the aforementioned characteristics are the time-series averages of the monthly cross-sectional means.

Interpretation: Size and age decrease and illiquidity and book-to-market increase as IV increases. There is an inverse U-shaped relation between both institutional ownership and momentum with IV.

IV Quintile	Size	Age	Illiq	Inst	BM	Mom
Low	1,708	14.2	41	0.25	0.40	0.06
2	2,015	15.4	91	0.34	0.53	0.09
3	1,284	12.7	185	0.33	0.58	0.09
4	675	10.5	437	0.26	0.62	0.05
High	235	9.1	1,941	0.15	0.74	-0.11

Table 15: Regressions of IV on Firm Characteristics

Description: This table reports regression estimates where IV-FF3 in month *t* is regressed on IV-FF3 and a series of firm characteristics in month *t*-1. The Fama and MacBeth (1973)–style regression is estimated on a monthly basis. The associated *t*-statistics, adjusted for heteroskedasticity and autocorrelation (Newey and West, 1987), are presented in the columns next to the coefficient estimates. The coefficients on illiquidity are multiplied by 1,000. All variables are winsorized at the 1st and 99th percentile. The sample period is April 1980 to December 2017. Panel A (B) reports output for equal- (value-) weighted regressions.

Interpretation: In all regression specifications, size and age are negatively related to IV and illiquidity is positively related to IV. Institutional ownership, book-to-market, and momentum have differing relations to IV across the regression specifications.

Panel A: Equal-Weighted Regressions				
Intercept	-0.850	(-25.01)	-2.055	(-31.26)
ln(IV)	0.569	(116.35)		
ln(size)	-0.060	(-32.46)	-0.130	(-29.78)
ln(age)	-0.020	(-13.43)	-0.049	(-14.11)
Illiq	0.017	(15.01)	0.057	(19.77)
Inst	-0.035	(-11.07)	-0.069	(-10.57)
ln(BM)	0.053	(22.90)	-0.122	(-23.32)
Mom	-0.048	(-7.17)	-0.098	(-6.52)

Panel B: Value-Weighted Regressions				
Intercept	-1.034	(-52.87)	-2.119	(-56.16)
ln(IV)	0.510	(108.42)		
ln(size)	-0.058	(-36.31)	-0.118	(-47.14)
ln(age)	-0.040	(-18.39)	-0.082	(-19.69)
Illiq	0.038	(14.56)	0.092	(16.50)
Inst	0.010	(2.60)	0.024	(3.33)
ln(BM)	-0.033	(-11.12)	-0.070	(-11.35)
Mom	0.004	(0.36)	-0.004	(-0.19)

Table 16: IV in Firm Characteristic Quintiles

Description: This table reports the level of IV-FF3 in firm characteristic–sorted quintiles. IV-FF3 is estimated monthly from the Fama-French (1993) three-factor model using daily returns. The series are value-weighted and reported as annualized standard deviations. Firm characteristics include size (market capitalization in millions of dollars), age (in years), the Amihud (2002) illiquidity ratio, institutional ownership, book-to-market ratio, and momentum over the last 12 months. The sample period in Panel A is July 1927 to June 1963 except for age, which starts in April 1946. In Panel B, the sample period is July 1963 to December 2017 except for institutional ownership, which starts in April 1980.

Interpretation: As size and age increase, IV decreases, and as illiquidity increases, IV increases. There is a positive relation between book-to-market and IV in Panel A. In Panel B, value firms have the highest IV followed by growth firms. With momentum, losers have the highest IV followed by winners. There is a decreasing trend in IV as institutional ownership increases.

Panel A: July 1927 to June 1963						
Quintile	Size	Age	Illiq	Inst	BM	Mom
Low	0.576	0.206	0.160		0.185	0.298
2	0.388	0.197	0.243		0.188	0.215
3	0.315	0.195	0.308		0.208	0.194
4	0.263	0.169	0.429		0.244	0.185
High	0.171	0.140	0.610		0.332	0.223

Panel B: July 1963 to December 2017						
Quintile	Size	Age	Illiq	Inst	BM	Mom
Low	0.626	0.330	0.213	0.280	0.239	0.390
2	0.484	0.304	0.296	0.292	0.222	0.250
3	0.392	0.290	0.338	0.264	0.222	0.212
4	0.314	0.259	0.410	0.236	0.230	0.211
High	0.212	0.202	0.624	0.251	0.270	0.273

Table 17: Firm Characteristics in IV Quintiles across Subperiods

Description: This table reports summary statistics for the full sample (all) and IV quintiles over subperiods spanning July 1926 to December 2017. Firm characteristics include inflation-adjusted size (market capitalization in millions of December 2017 dollars), age (in years), and the Amihud (2002) illiquidity ratio (multiplied by one million). All variables are winsorized at the 1st and 99th percentile. Each month, stocks are sorted into quintiles based on IV-FF3 estimated using the Fama and French (1993) three-factor model. The reported means of the aforementioned characteristics are the time-series averages of the monthly cross-sectional means.

Interpretation: For the full sample, inflation-adjusted size and age increase and illiquidity decreases in the post-CLMX period. So, from the 1990s to the 2000s and then to the 2010s. These same patterns are observed in all IV quintiles for illiquidity and in IV quintiles two to five for size and age.

	All	Low	2	3	4	High
Panel A: Inflation-Adjusted Size						
1926–2017	1,320	2,899	1,833	1,072	571	227
1926–1930	1,100	3,016	1,237	704	383	164
1931–1940	809	2,743	731	330	166	83
1941–1950	725	2,219	656	381	243	130
1951–1960	1,526	3,778	1,690	1,110	710	347
1961–1970	1,877	5,240	2,152	1,151	590	255
1971–1980	944	2,298	1,380	638	288	115
1981–1990	761	1,660	1,251	568	243	85
1991–2000	1,230	2,647	2,000	918	430	157
2001–2010	1,967	2,913	3,408	2,072	1,078	362
2011–2017	2,492	2,386	4,214	3,321	1,868	669
Panel B: Age						
1926–2017	12.6	14.4	14.5	12.6	11.0	10.3
1926–1930	2.4	2.5	2.4	2.3	2.3	2.5
1931–1940	8.1	8.4	7.8	7.6	7.8	8.7
1941–1950	14.5	15.7	14.4	13.8	13.7	14.9
1951–1960	19.7	20.7	19.9	19.4	18.8	19.7
1961–1970	14.7	20.8	18.0	14.8	11.4	8.6
1971–1980	11.0	12.3	14.3	11.6	9.1	7.5
1981–1990	11.2	14.5	14.8	11.3	8.7	7.0
1991–2000	11.0	16.4	13.7	9.7	7.8	7.5
2001–2010	13.4	14.1	16.1	14.0	12.1	10.7
2011–2017	14.7	11.3	17.9	17.1	14.9	12.3
Panel C: Illiquidity Ratio						
1926–2017	973	85	204	426	939	3,214
1926–1930	1,039	59	134	286	790	3,931
1931–1940	3,555	212	725	1,799	4,214	10,834
1941–1950	1,268	184	342	588	1,070	4,160
1951–1960	318	79	132	180	261	937
1961–1970	600	86	154	260	499	1,999
1971–1980	590	38	115	245	534	2,018
1981–1990	677	69	147	281	604	2,284
1991–2000	800	40	95	213	534	3,121
2001–2010	453	26	62	135	352	1,691
2011–2017	255	31	54	98	244	849