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# IDIOSYNCRATIC EQUITY RISK TWO DECADES LATER

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## ABSTRACT

This paper reviews the literature on idiosyncratic equity volatility since the publication of "Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk" in 2001. We respond to replication studies by Chiah, Gharghori, and Zhong and by Leippold and Svaton, and we present volatility estimates through the end of 2021, significantly extending the period covered in our original paper as well as the two replication studies. After spiking in the 1999-2000 period, idiosyncratic volatility declined thereafter; but sharp increases in market, industry, and idiosyncratic volatility occurred during the global financial crisis of 2008-2009 and the COVID-19 pandemic of 2020-2021. We argue that market microstructure effects are not of first-order importance for volatility measurement, and we discuss the roles of fundamental factors and investor sentiment in driving the observed fluctuations in volatility.

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## 1. Introduction

Our paper "Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk" (Campbell, Lettau, Malkiel, and Xu 2001, henceforth CLMX) made three main contributions to the finance literature. First, it directed the attention of the finance profession to idiosyncratic firm-level volatility in stock returns. Even though idiosyncratic volatility can be diversified away, many investors hold concentrated portfolios—either by choice or through executive compensation schemes—and thus are exposed to firm-level risk. Idiosyncratic volatility also serves as an empirical proxy for the flow of firm-specific information and for the risk of human capital specialized to meet the needs of a particular firm, and it reflects important corporate decisions, including leverage and diversification of project-level risk within corporations.

Second, CLMX proposed a simple way to measure cross-sectional average idiosyncratic volatility instead of the idiosyncratic volatility of particular firms. For any particular firm, measuring idiosyncratic volatility requires first measuring the beta of the firm with the market, and possibly also other betas with industry or style factors. On average, however, this is not required because the average market beta, across the entire cross-section of firms, equals one whenever the same weights are used to average betas as are used in the construction of the market index.

Third, CLMX showed that average idiosyncratic volatility increased relative to the volatility of a market index during the July 1962 to December 1997 sample period. This implied that the average correlation of returns across firms had declined, and the number of stocks required to deliver a target level of portfolio risk had increased.

We are grateful for the subsequent interest in idiosyncratic volatility in general, and CLMX in particular. We especially appreciate the careful replication studies by Chiah, Gharghori, and Zhong (2020, henceforth CGZ) and Leippold and Svatoň (2021, henceforth LS). In this short note, we first (in section 2) discuss the volatility movements that have occurred since the end of our original sample period. We use data through 2021, significantly extending the samples used by LS and CGZ which end in 2016 and 2017 respectively. Then (in section 3) we discuss the market microstructure issues raised by LS. Finally (in section 4), we discuss the broader economic questions raised by the dynamics of idiosyncratic equity volatility. Section 5 briefly concludes.

## 2. Idiosyncratic Volatility in Recent Data

Since the publication of CLMX, many papers have updated the analysis. We cite in particular Brown and Kapadia (2007), who look at data through 2004, Brandt, Brav, Graham, and Kumar (2010) and Bekaert, Hodrick, and Zhang (2012) who look at data through 2008, Herskovic, Kelly, Lustig, and Van Niewerburgh (2016), who look at data through 2010, Campbell (2018, Chapter 2) who looks at data through 2012, and Bartram, Brown, and Stulz (2019) who look at data through 2017. These papers emphasize a decline in idiosyncratic volatility that occurred in the 2000s after the end of the technology boom of the late 1990s.

We emphasize that such a decline in no way contradicts the findings of CLMX. We considered several econometric models but found that the rise in idiosyncratic volatility during our 1962 – 1997 sample was best captured by a trend-stationary AR(1) model with a linear trend. Of course, a stochastic process with a trend is an unreasonable model of the true data generating process for volatility because a downward trend eventually implies negative volatility, which is mathematically impossible, and an upward trend eventually implies economically implausible levels of risk. While a linear trend was a good description of the increase in idiosyncratic volatility in our sample period, we did not believe that the positive trend would necessarily continue in extended samples.

Nonetheless, it is interesting to ask what the history of volatility looks like if we consider a longer sample period, beginning in 1926 (as CGZ do) and continuing through the Covid-19 pandemic to the end of 2021. Monthly market (MKT), industry (IND), and firm (FIRM) volatilities are constructed as in CLMX as the sum of squared daily returns from the Center for Research in Security Prices (CRSP). Instead of plotting variances as in CLMX, we plot standard deviations since they are easier to interpret. The figures in this paper show annual volatilities constructed by summing monthly variances in a year and then taking the square root. Figure 1 sets the stage by plotting the total volatility of a typical stock, i.e. the square root of the sum of market variance, industry variance, and idiosyncratic firm-level variance. The top panel of the figure value weights firms (the base case in CLMX), while the bottom panel equal weights them (an alternative case also considered by CLMX). The CLMX sample period, 1962–1997, is shaded in grey in each panel.

The uptrend in total volatility is clearly visible during the CLMX sample period, moderate when firms are value-weighted and strong when they are equal-weighted. The data from 1926 to 1962, which we did not consider in CLMX because daily CRSP data were not then available before 1962, shows extremely high volatility during the Great Depression, declining gradually to a low and stable level after World War II. There is nothing particularly unusual about the starting date of the CLMX sample period relative to other years in the 1950s and 1960s. Since 1997, total volatility has remained high on average, with periodic upward spikes during the technology boom and bust around the turn of the millennium, the global financial crisis in 2008-2009, and most recently the COVID-19 pandemic and accompanying speculation in so-called “disruptive innovation” and “meme” stocks in 2020-2021.

Figure 2 breaks total value-weighted volatility into the three components defined by CLMX: market volatility in the top panel, industry volatility in the middle panel, and idiosyncratic firm-level volatility in the bottom panel. Figure 3 does the same for equal-weighted volatility.

During the CLMX sample period from 1962 to 1997, we see the developments emphasized by CLMX: transitory variation in market volatility with no long-term trend, a modest upward trend in industry-level volatility, and a stronger upward trend in idiosyncratic volatility. The upward trend in idiosyncratic volatility is particularly dramatic when the data are equal-weighted, but is also present in value-weighted data.

In the period from 1926 to 1962, we see extremely high levels of all volatilities during the Great Depression, followed by gradual declines in all volatilities to low levels during and after World War II. The relatively low market volatility during a major war is a known phenomenon sometimes called the "war puzzle" (Schwert 1989, Cortes, Vossmeyer, and Weidenmier 2022). CGZ show similar patterns in their study of the earlier data.

In the years since 1997, the three volatilities have fluctuated in tandem, with common spikes and intervening quiet periods. The average levels of both market and industry volatility are high relative to the CLMX sample period: for example, value-weighted market volatility has averaged 18% since 1997 but only 12% during the CLMX period, while value-weighted industry volatility has averaged 14% since 1997 but only 9% during the CLMX period. The average level of value-weighted idiosyncratic volatility since 1997 is 28%, lower than the levels reached at the end of the CLMX period but still slightly higher than the average of 26% during that period. Idiosyncratic volatility was low for several years in the 2000s after the end of the 1990s technology boom—the point emphasized by Brandt, Brav, Graham, and Kumar (2010) and Bekaert, Hodrick, and Zhang (2012)—but it has risen again in subsequent crises. The last few years of elevated idiosyncratic volatility are not discussed by CGZ or LS since these data fall outside the sample periods they consider.

For some purposes, it is interesting to look not at the absolute levels of volatility but at the shares of the total variance of a typical stock accounted for by market variance, industry variance, and idiosyncratic firm-level variance. We show these shares in Figure 4, value weighting stocks in the top panel and equal weighting them in the bottom panel. In the top panel, we see that the CLMX sample period was characterized by gradually declining shares of market and industry variance and a gradually increasing share of firm-level variance. The share of firm-level variance was between 60% and 80% throughout this period.

Since 1997, the share of market variance has increased considerably. From a low of 10% in the late 1990s it briefly reached 40% during the global financial crisis and is around 30% in the most recent data. The share of industry variance is also somewhat higher than during the CLMX sample period, and the share of firm-level variance is accordingly lower: below 50% in the global financial crisis and around 60% in the most recent data. Variance shares in the recent data look more like the period 1926 – 1962 than like the CLMX period 1962–1997, even though the absolute levels of volatility have never attained the extreme levels experienced during the Great Depression. Comparing Figure 4 with Figures 2 and 3 makes clear that this shift in variance shares has occurred primarily because market and industry volatility have increased in the last two decades, not because firm-level volatility has declined.

In equal-weighted data, shown in the bottom panel, the share of firm-level variance has remained extremely high, but again it has declined from about 95% at the end of the CLMX sample period to around 80% in the latest data. The recent equal-weighted data appear comparable to the early part of the CLMX sample period.

Another way to describe the relative importance of different types of volatility is to calculate the average correlation between two individual stocks, or the average explanatory power ($R^2$ statistic) of a market-model regression for an individual stock. CLMX plotted time series for both these quantities, and found them to be highly similar. They would be exactly identical in a market with identical stocks all having the same variances and the same correlations with one another; while the real-world data do not satisfy these assumptions, the differences across stocks average out in such a way that the differences between average correlation and average $R^2$ are negligible.

In Figure 5, we plot the value-weighted average correlation in the top panel and the equal-weighted average correlation in the bottom panel. We do not plot the average $R^2$ statistic from a market-model regression because we have verified that, as in CLMX, this is almost identical to the average correlation. Within each panel, we do compare the average correlation of daily returns within a year to the average correlation of weekly returns within the year. In earlier data, the weekly correlations are somewhat higher, reflecting lead-lag effects in daily returns of the sort emphasized by Lo and MacKinlay (1990), but differences are small in data from the last three decades.

The decline in average correlation emphasized by CLMX is visible in the shaded areas of each panel. Before the CLMX sample period, the average correlation was much higher on average with extreme spikes during episodes of high market volatility in the Great Depression. Since the end of the CLMX sample period, the average correlation has risen with spikes during the global financial crisis and the COVID-19 pandemic. Individual stocks are typically more correlated with one another today than they were in the 1990s. Mechanically, this primarily reflects elevated market volatility rather than reduced idiosyncratic firm-level volatility.

### 3. Market Microstructure and Volatility Measurement

CLMX measured volatility using daily close-to-close returns from the CRSP database, and we followed the same procedure in the previous section of this note. LS and Lesmond et. al. (2020) argue that it would be more appropriate to use the midpoint between bid and ask quotes, which they describe as efficient prices. They argue that midpoint prices follow a random walk even if transaction prices show transitory variation as transactions occur randomly at ask quotes above the midpoint, or bid quotes below the midpoint. As Roll (1984) pointed out, such “bid-ask bounce" can increase the volatility of high-frequency returns measured using transaction prices.

For a number of reasons, we believe that closing transaction prices are appropriate to use in the calculation of volatility. For exchange-traded stocks, the closing price is determined by a closing auction. The closing auction is the busiest time in the trading day. Literally hundreds of millions of stocks are traded, about 7 percent of daily volume. All institutions that report on a daily basis use the closing auction price to value their portfolios. Mutual funds use that single closing price to determine the value of the purchases and redemptions of mutual fund shares made during the day. As a clearing price for the large number of market participants who trade with "market on close" orders, the closing price effectively does represent the midpoint between buying and selling interests.

More generally, purchasers of stocks generally pay ask prices, while sellers get bid prices. To be sure, some transactions are "crossed" at the midpoint, but where waves of buying or selling occur, transactions prices are typically at bid or ask prices. One statistic popular on Wall Street is "up volume vs. down volume." On days when the market rises sharply, up volume (trades at an uptick) greatly exceeds down volume (trades at a downtick). When there is a sharp decline, the opposite is true. On such days, most trades are transacted at either bid or ask prices. To measure volatility using quote midpoints can bias volatility downward and mask the instability of transactions prices.

Moreover, spreads widen in volatile markets and for individual stocks when they become more volatile. Hence the LS approach introduces a greater downward bias in measured volatility during especially volatile trading days.

When returns are serially correlated, the volatility of returns—annualized in the standard fashion—varies with the holding period over which returns are measured. There is a term structure rather than a single level of volatility. But transaction costs, of the sort modeled by LS, are neither necessary nor sufficient for such serial correlation to arise. Transaction costs are not necessary because serial correlation can be generated by market mispricing or time-varying risk premia rather than by market microstructure effects; and transaction costs are not sufficient because market microstructure models in which trades move quotes, such as the canonical model of Glosten and Milgrom (1985), have both costly trading and random-walk transaction prices.

Ultimately it is an empirical question how annualized volatility varies with the holding period. In CLMX, we looked at daily, weekly, and monthly holding periods and found similar time-series variation at all three holding periods, with only a slightly weaker upward trend in firm-level volatility for longer holding periods. The precision of volatility estimates declines with the holding period, so we did not look beyond one month. A literature on stock return forecastability has argued that there are further changes in the annualized volatility of the aggregate market at longer horizons (Campbell 1991, Cochrane 1994, Campbell, Chan, and Viceira 2003), but these effects appear to be much weaker in individual stock returns (Vuolteenaho 2002), so we doubt that they are important for the main conclusion of CLMX.

In Figures 6 and 7, we show how Figures 2 and 3 change when we correct daily volatilities for the first-order autocorrelation of returns by adding twice the first daily autocovariance to the daily variance, or when we use a week as our base return interval rather than a day. These two adjustments have very similar effects, implying that daily autocovariances beyond the first are extremely small. The adjustments have larger effects on the equally weighted series in Figure 7 than on the value-weighted series in Figure 6, reflecting stronger (further from zero) autocorrelations in the returns on small stocks.

In the CLMX period and particularly in the pre-CLMX period, the adjusted market volatility series are slightly higher than the unadjusted series. The adjusted industry and idiosyncratic volatility series, on the other hand, are slightly lower than the unadjusted series. During the last two decades, the adjustments have a minimal impact. The adjustments are consistent with the firstorder daily autocorrelations of returns, which we calculate separately in each year. The autocorrelations of market, industry, and firm volatilities are plotted in Figure 8. Market returns are positively autocorrelated at the daily frequency until the late 1990s, a fact emphasized by Froot and Perold (1995). Industry and firm-level returns are weakly negatively autocorrelated in the pre-CLMX sample period, but have had little autocorrelation in recent decades. Hence, any potential market-microstructure effects on volatility are more likely to matter for market volatility rather than volatilities of industry and firm-level returns. Overall, the autocorrelations in returns are modest—particularly at the industry and firm-level—and do not have first-order effects on the volatility trends discussed by CLMX or the movements in volatility that have occurred more recently.

LS make one point that would lead us to undertake further empirical analysis if we were to repeat the analysis of CLMX in full detail. CLMX include NASDAQ stocks from the inception of the NASDAQ stock market in February 1971. LS point out that from 1971 to 1982, all NASDAQ prices recorded in the CRSP database were quote midpoints, and from 1982 to 1992, the NASDAQ prices for small-cap stocks in CRSP were still quote midpoints. We have argued against the use of quote midpoint prices, so ideally, we should adjust the volatilities that result from these NASDAQ prices. However, any such adjustment would have only a modest effect on the findings of CLMX. The quote midpoint problem affects only the NASDAQ, which accounted for only about 15% of the combined market cap of the NYSE, AMEX, and NASDAQ during the 1970s and 1980s. Hence, even excluding NASDAQ stocks in the 1970s and 1980s (which we do not believe would be an appropriate solution to the problem because these relatively volatile stocks are legitimate constituents of the aggregate US stock market) has only a modest effect on value weighted volatility trends. Even more simply, we note that the uptrend in idiosyncratic volatility is visible in a comparison of the 1960s with the 1990s, excluding the 1970s and 1980s altogether.

## 4. The Economic Interpretation of Idiosyncratic Volatility

The most interesting question raised by CLMX is what causes the time-series variation in average idiosyncratic volatility that we identified. The economic forces driving volatility fall into two broad categories, related to firm fundamentals and investor sentiment, respectively. In the language of Campbell (1991), fundamentals determine the volatility of cash-flow news, while investor sentiment drives the volatility of discount-rate news.

Fundamental forces driving idiosyncratic volatility include the age of publicly traded firms, since young firms are often developing new technologies with uncertain prospects (Pástor and Veronesi 2003), and the size and diversification of these firms, since large conglomerates diversify profits across projects and industries. The level of competition may also matter, since cartelized industries may allocate stable profit shares to indidvidual firms, reducing firm-level volatility relative to industry and market volatility. Morck, Yeung, and Yu (2000) argue that in emerging markets, idiosyncratic volatility is low relative to market volatility in part because conglomerates and cartels are common in emerging economies.

These fundamental factors may also be relevant for the US time series studied by CLMX. The original CLMX sample period was an era in which conglomerates fell out of fashion. Since the end of the CLMX sample, the strong increase in firm-level volatility in the late 1990s accompanied an IPO boom, and the subsequent decline in firm-level volatility in the 2000s occurred during an IPO bust. There is also widespread concern that the level of competition in the US economy has declined during the early 21st century.

Investor sentiment can also affect idiosyncratic volatility, particularly over shorter holding periods. Consistent with this, periods of high idiosyncratic volatility often begin during periods of elevated stock prices and intense retail trading activity. During these periods, there is often evidence of extreme optimism and speculation among stock market participants, and idiosyncratic volatility remains high during the inevitable corrections that follow. Conversely, a shift towards passive investment management may be a longer-term factor tending to reduce idiosyncratic volatility.

To illustrate the plausibility of both fundamentals and investor sentiment as drivers of average idiosyncratic volatility, the top panel of Figure 9 plots idiosyncratic volatility against the number of stocks in the market, while the bottom panel plots it against the cyclically adjusted price-earnings or CAPE ratio (Campbell and Shiller 1988). The common movements in these series are clearly visible, both during and after the original CLMX sample period. For example, the spikes in volatility in 19990-2000 and 2020-2021 both accompanied increases in the CAPE ratio.

The most thorough recent empirical study of the time-series variation in average idiosyncratic volatility is Bartram, Brown, and Stulz (2019). This paper argues that the average age, size, and liquidity of publicly traded firms jointly explain most of the time-series variation in idiosyncratic volatility. The first two of these factors are clearly fundamental, while the last may be related to investor sentiment.

Of course, there is a limit to what can be learned from time-series comovement in aggregate state variables. Several recent papers have instead looked at cross-sectional patterns, some of which point towards the importance of investor sentiment. Brandt, Brav, Graham, and Kumar (2009), for example, show that the increase and reversal of idiosyncratic volatility in the late 1990s and early 2000s was concentrated in firms with low prices per share and high retail ownership.

Regardless of the causes of idiosyncratic volatility, it clearly matters to undiversified investors because these investors are exposed to idiosyncratic risk in their portfolios as pointed out by Merton (1987). There is a large empirical literature asking how cross-sectional and time-series variation in idiosyncratic volatility is related to subsequent stock returns.

In the cross-section, Ang, Hodrick, Xing, and Zhang (2006, 2009) show that stocks with recently high realized idiosyncratic volatility tend to have low subsequent returns. This observation is consistent with the idea that volatile stocks have an over-optimistic retail investor clientele and are accordingly overvalued. However, other measures of idiosyncratic volatility, such as forecast idiosyncratic volatility from an EGARCH model (Fu 2009), the volatility of a size- and beta-sorted portfolio corresponding to each firm (Malkiel and Xu 2002), or a long-run persistent component of idiosyncratic volatility (Cao and Xu 2010) appear to be associated with high subsequent returns. This may be because these measures better capture the component of idiosyncratic volatility that is priced in undiversified portfolios and are less correlated with the component of volatility that reflects over-optimism of the investor clientele. There is an active debate about these cross-sectional patterns with further contributions by Bali and Cakici (2008), Bali, Cakici, and Whitelaw (2011), Han and Lesmond (2011), and Huang, Liu, Rhee, and Zhang (2010).

In the time-series, Goyal and Santa-Clara (2003) argue that average idiosyncratic volatility predicts future excess returns on the aggregate stock market, but Bali, Cakici, Yan, and Zhang (2005) show that this result is sensitive to several features of their particular specification. Herskovic, Kelly, Lustig, and Van Niewerburgh (2016) argue that idiosyncratic volatility is related to the risk in the human capital of individual households, because workers form specialized matches with employers and their compensation is therefore sensitive to the fortunes of their employers. Accordingly, changes in the average level of idiosyncratic volatility should be a priced risk factor, and this helps to explain a number of otherwise puzzling patterns in asset returns.

## 5. Conclusion

We have examined the behavior of volatility at the market, industry, and firm level over a period of almost 100 years. We find that the increase in idiosyncratic volatility during the CLMX sample period of 1962-1997 began in the early 1950's and continued until 2001, when it dropped sharply. Firm-level volatility spiked during the financial crisis and has been rising towards the end of our sample in 2021. A main difference between volatility patterns today and those of the late 1990s is not that idiosyncratic volatility is lower, but that industry and, in particular, market volatility are higher. We found little evidence that market-microstructure issues have significant impacts on the volatility measure studied in CLMX.

Both fundamental forces—such as the age and size of individual firms—and fluctuations in investor sentiment have been adduced in the literature to explain changes in volatility. We believe that both types of factors are important, with fundamental forces operating at lower frequencies and fluctuations in sentiment particularly important at higher frequencies. The spikes in volatility during the "dot.com" boom in the late 1990s and the COVID-19 pandemic in 2020–2021 are both plausibly driven by investor sentiment. Disentangling these influences is an important task for future research.

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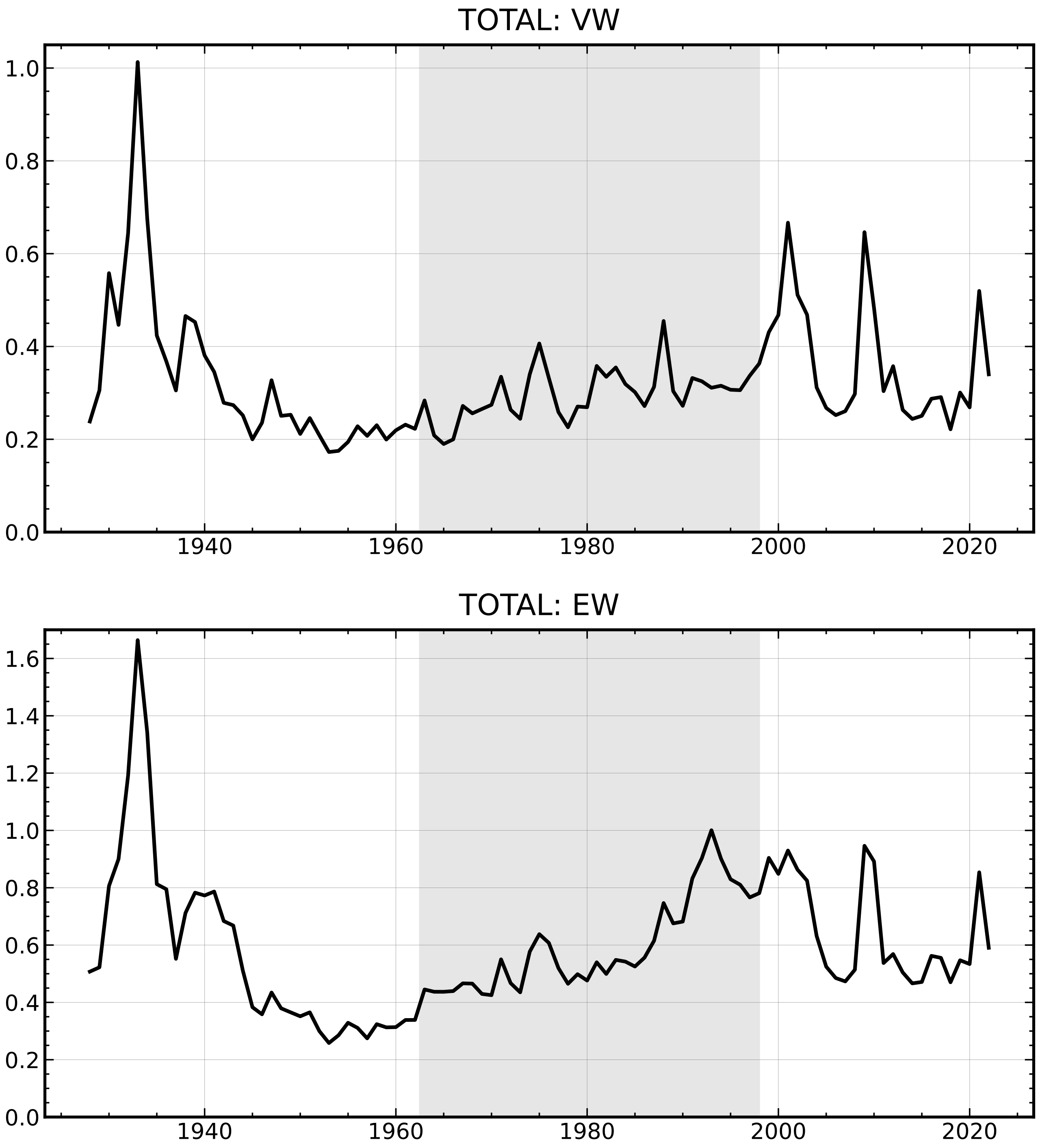
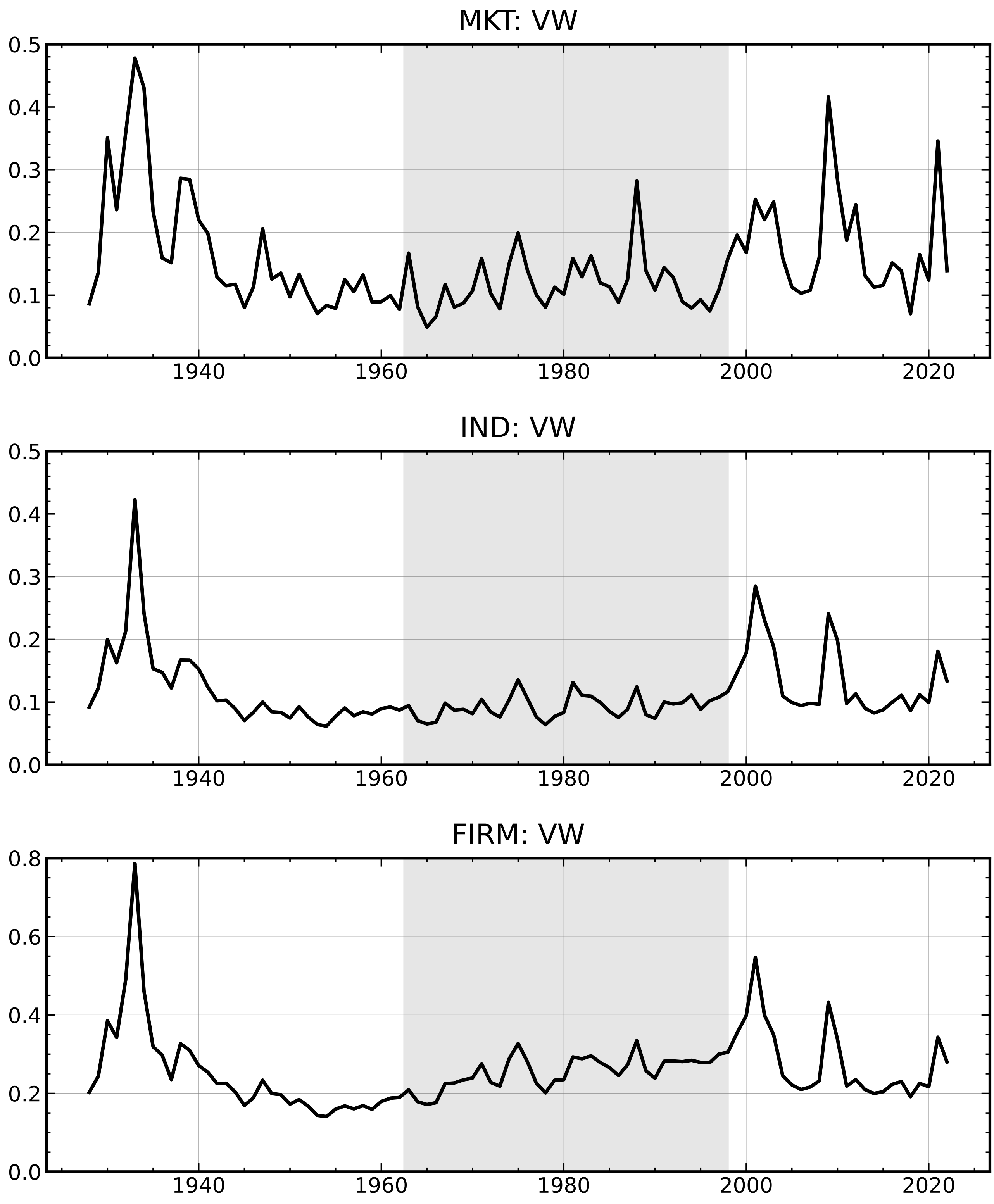
**Figure 1:** Total Volatility from Daily Data



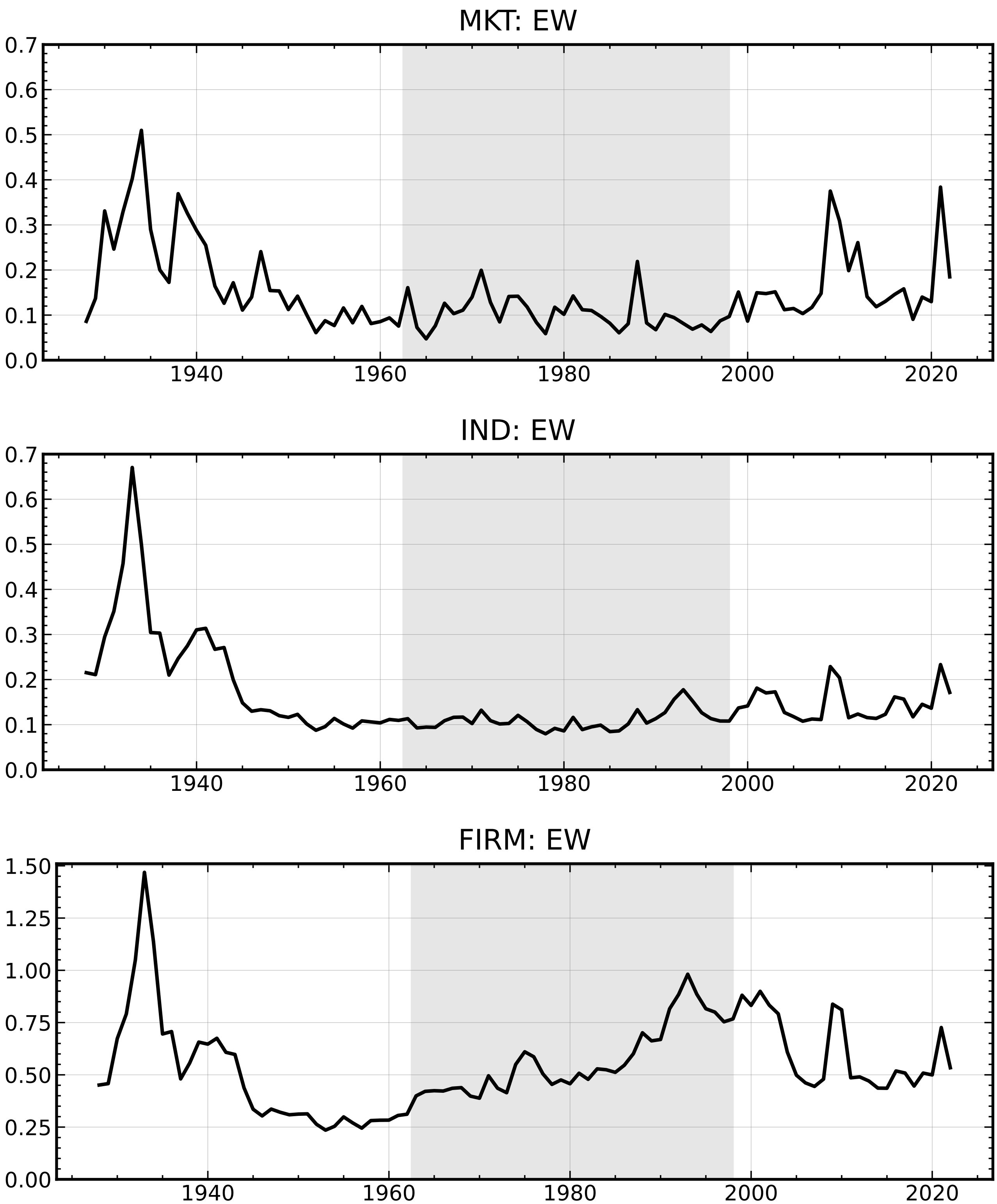

Notes: The figure plots the square root of the annual total variance of an average stock. The total variance is defined as TOTAL=MKT+IND+FIRM. The top panel shows the value-weighted total volatility, while the bottom panel shows equal-weighted total volatility. Monthly variances are the sum of daily squared returns within a month and annual variance are the sum of monthly variances in a year. The sample period is 1927 to 2021.

**Figure 2:** Value-weighted Volatilities from Daily Data



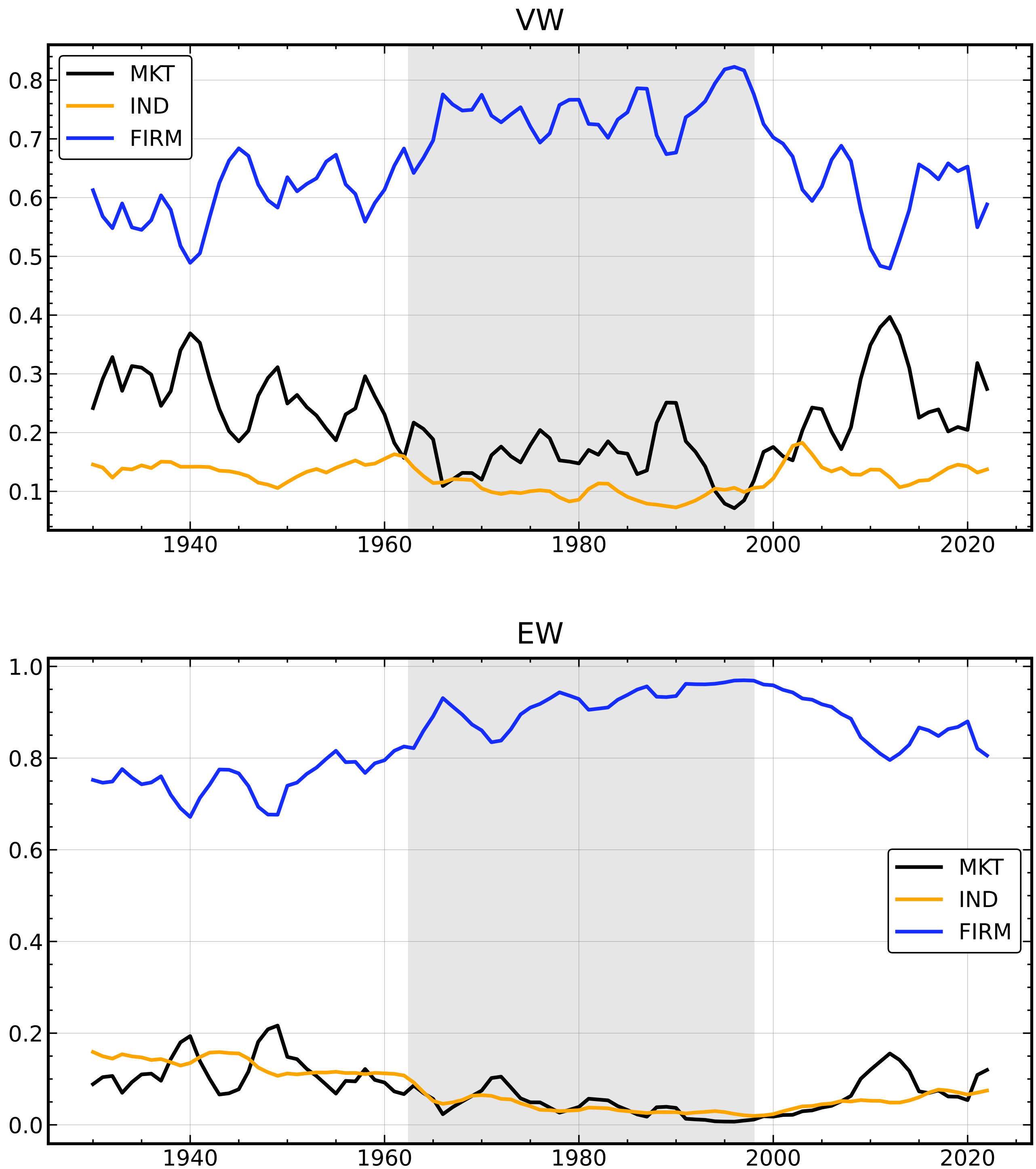

Notes: The figure plots the standard deviations of value-weighted market, industry, and firm volatilities. Monthly variances are the sum of daily squared returns within a month and annual variance are the sum of monthly variances in a year. The sample period is 1927 to 2021.

**Figure 3:** Equal-weighted Volatilities from Daily Data



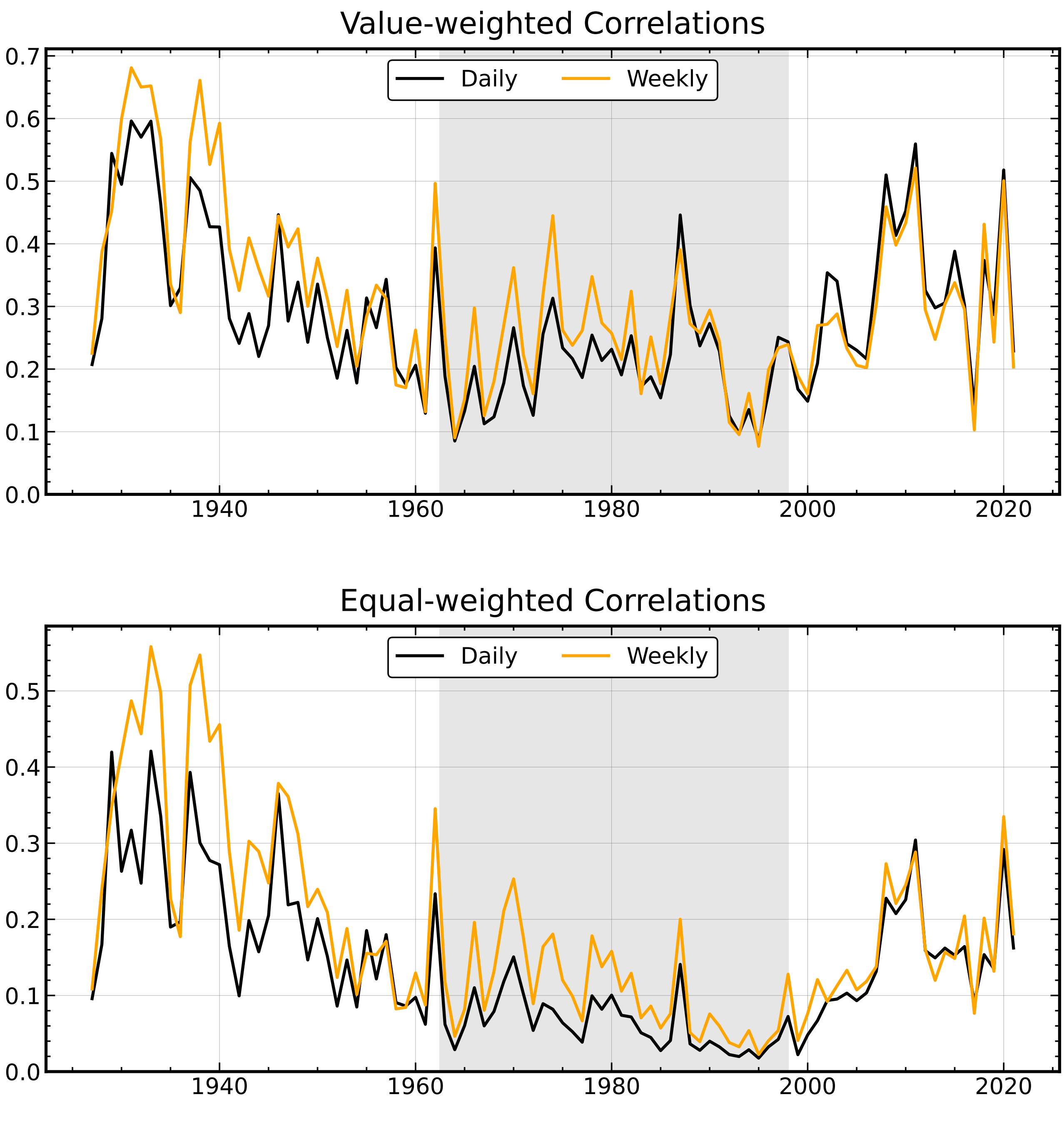

Notes: The figure plots the standard deviations of equal-weighted market, industry, and firm volatilities. Monthly variances are the sum of daily squared returns within a month and annual variance are the sum of monthly variances in a year. The sample period is 1927 to 2021.

**Figure 4:** Shares in Total Variance



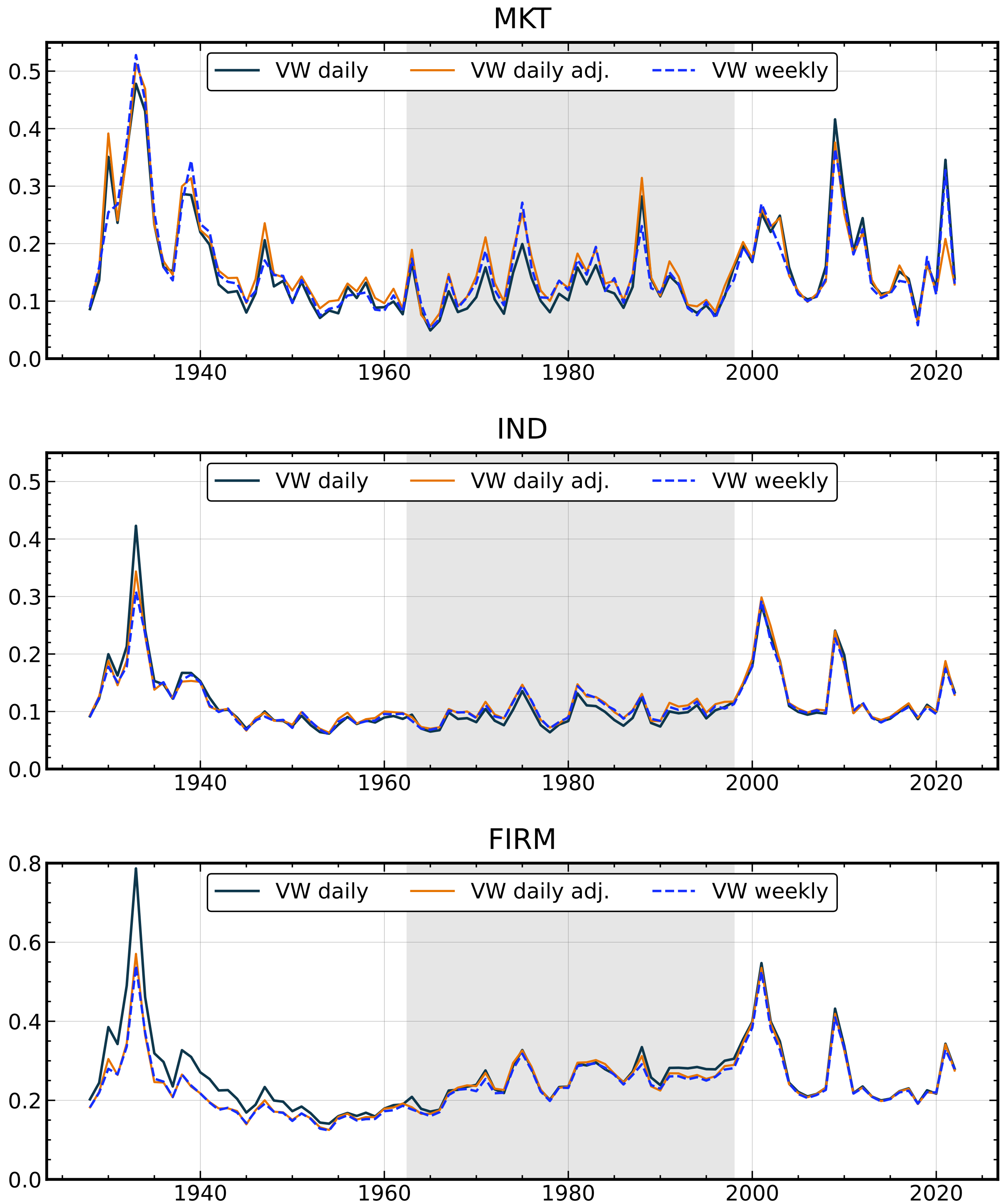

Notes: The figure plots the shares of market, industry, and firm volatilities in total volatility. The top panel shows the value-weighted total volatility, while the bottom panel shows equal-weighted total volatility. Monthly variances are the sum of daily squared returns within a month and annual variance are the sum of monthly variances in a year. The sample period is 1927 to 2021.

**Figure 5:** Average Stock Correlations



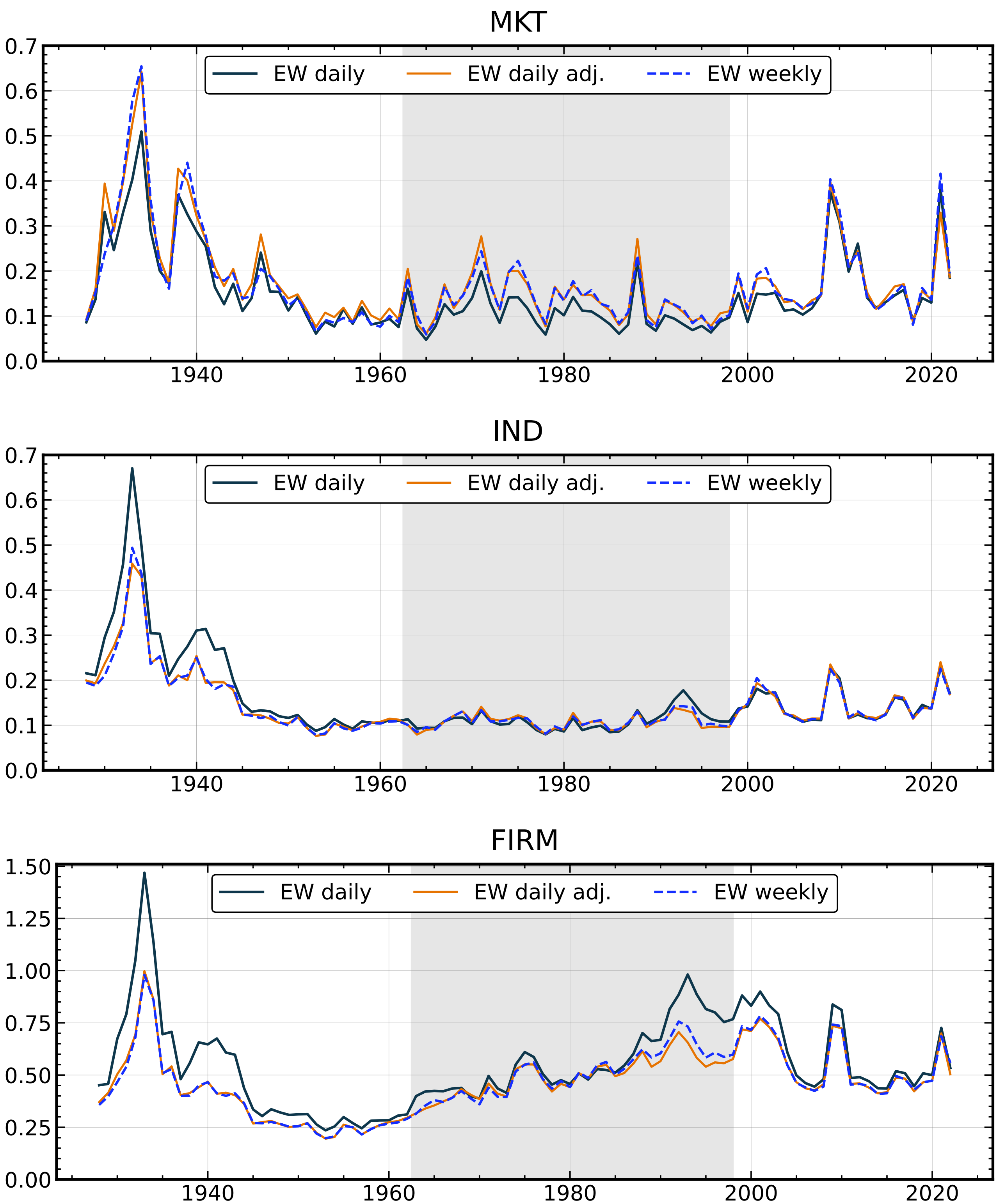

Notes: The top panel reports average pairwise correlations across stocks based on daily and weekly returns within a year. The top panel shows value-weighted correlations, while the bottom panels shows equal-weighted correlations. Stocks included in the calculation at each point in time are required to have a complete return history within a year. The sample period is 1927 to 2021.

**Figure 6:** Alternative Value-weighted Volatilities



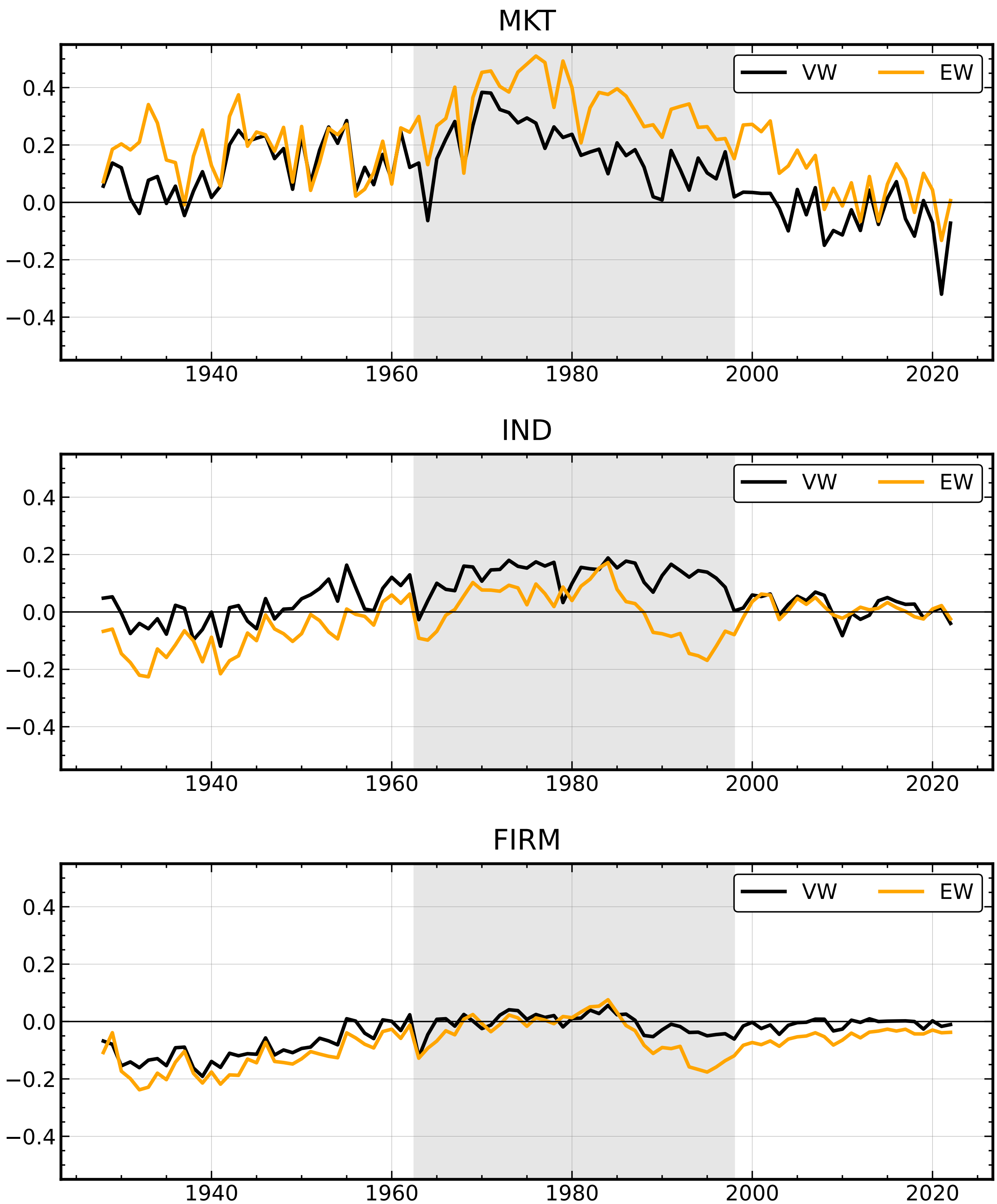

Notes: The figure plots alternative measures of value-weighted market, industry, and firm volatilities. The black line shows the square root of the sum of daily squared returns within a year. The blue line shows autocorrelation-adjusted variances defined as the sum of daily squared return plus two times the product of daily returns and daily returns lagged by one day. The orange line shows the square root of the sum of weekly squared returns within a year. The sample period is 1927 to 2021.

**Figure 7:** Alternative Equal-weighted Volatilities



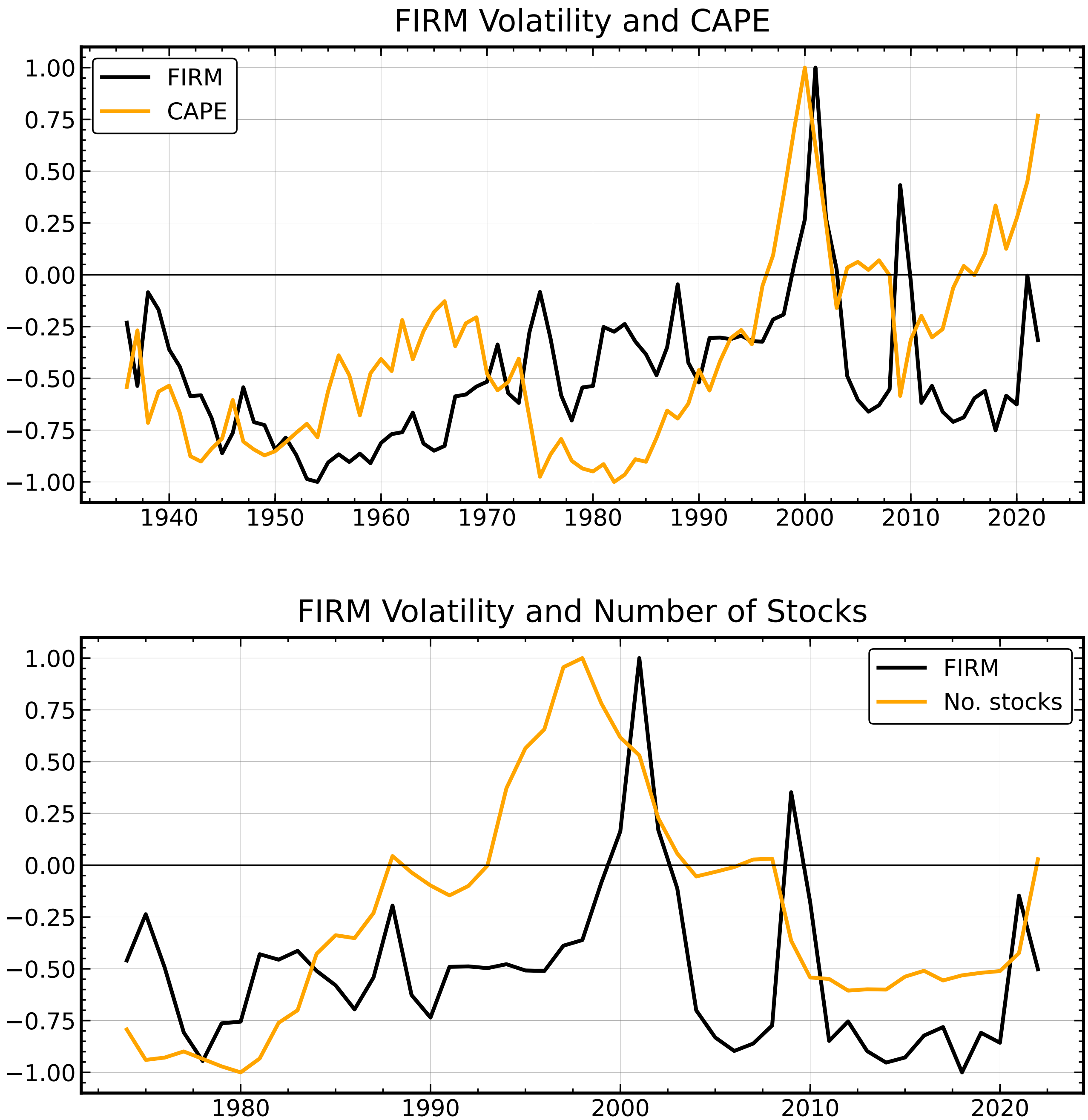

Notes: The figure plots alternative measures of equal-weighted market, industry, and firm volatilities. The black line shows the square root of the sum of daily squared returns within a year. The blue line shows autocorrelation-adjusted variances defined as the sum of daily squared return plus two times the product of daily returns and daily returns lagged by one day. The orange line shows the square root of the sum of weekly squared returns within a year. The sample period is 1927 to 2021.

**Figure 8:** Annual Autocorrelations of Daily Returns




Notes: The figure plots annual first-order autocorrelations of daily returns. The construction of the MKT, IND, and FIRM autocorrelations follows the corresponding definitions of MKT, IND, and FIRM volatilties. Value-weighted autocorrelations are shown in black and equal-weighted Autocorrelations are in orange. The sample period is 1927 to 2021.

**Figure 9:** FIRM Volatility, CAPE, and Number of Stocks




Notes: The figure plots FIRM volatility and Shiller's CAPE ratio in the top panel and the number of listed stocks NYSE, AMEX, and NASDAQ in the bottom panel. The time series are normalized to be in the $[-1, 1]$ interval. The sample period is 1927 to 2021.