Yes, U.S. Stocks are Getting Riskier[☆,☆☆]

Gregory W. Brown[1], William Waller[2,3]

Abstract

Over the last few decades U.S. stocks have become significantly more volatile. This result holds even when excluding the financial crisis period of 2008-2009. Both the market index and individual stocks have become more volatile indicating that higher volatility is not just the result of higher idiosyncratic risk or increased correlations among stocks. Instead, the increase in risk is due entirely to more frequent and more extreme spikes in volatility. We find that after decomposing volatility into a long-run component and a transitory component, there is no meaningful trend in the long-run component. In contrast, our measure of transitory volatility has tripled over the last 40 years. The upward trend in the transitory component is primarily the result of changing characteristics of the typical publicly-traded firm due to the appearance of many new and riskier firms (e.g., technology stocks). Our findings show that the expansion of U.S. stock markets in recent decades has fundamentally altered the types of risks born by equity investors.

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[1] Sarah Graham Kenan Distinguished Scholar of Finance, Department of Finance, Kenan-Flagler Business School, The University of North Carolina–Chapel Hill, CB 3490, McColl Building, Chapel Hill, NC 27599-3490 USA, 919.962.9250, gregwbrown@unc.edu, and Director of Research, Smith-Breeden Associates.
[2] Department of Finance, Kenan-Flagler Business School, The University of North Carolina–Chapel Hill, CB 3490, McColl Building, Chapel Hill, NC 27599-3490 USA, 919.636.4908, william_waller@unc.edu.
[3] Corresponding Author

1. Introduction

Previous research has shown that individuals appear to form strong attitudes about stock market volatility that are quite persistent. For example, following the stock market declines during the Great Depression, households substantially reduced their holdings of equities. For decades stocks were even considered by many as risky bets inappropriate for prudent investors (Shiller, Fischer, and Friedman, 1984; Malmendier and Nagel, 2011). Even as the U.S. economy grew through the 1940s and 1950s, few new companies undertook public offerings of stock and the number of publicly traded issues grew slowly. As a consequence, during the middle of the last century, the value of publicly traded equity as a percent of GDP declined from an average of 62.7% in 1929 to a low of 17.8% in 1942 and stayed below the 1929 level until the early 1960s. Over the 1960s and 1970s the number of issues and total stock market capitalization increased sporadically as interest in equity investing recovered.[4]

However, the last few decades have witnessed dramatic shifts in the U.S. equity markets.[5] For example, the number of publicly traded companies jumped from less than 5,000 to over 9,000 during the technology boom of the late 1990s. After the bursting of the tech bubble the number of issues has declined to under 6,000. Likewise, market capitalization as a percent of GDP increased from 42.8% in 1980 to a peak of 170.1% in 2000 before falling to 89.0% of GDP in 2009 after the financial crisis. Surprisingly though, even at the recent trough, market capitalization as a percent of GDP is greater than in every year prior to 1996.

Not coincidentally, the last 30 years has also witnessed notable changes in the percent of households investing in stocks. According to the Survey of Consumer Finance (SCF), the percentage of households with direct or indirect stock holdings has increased from 19.0% in 1983 to over 51.1% in 2007.[6] This change in stock investing behavior is also reflected in households' perceptions of risk. The percentage of SCF respondents willing to take above average or substantial risk increased

[4]Sources: U.S. Commerce Department Bureau of Economic Activity, The Center for Research in Security Prices.

[5]These changes are likely due to any variety of factors ranging from changes in the investor base, to deregulation, to advances in information technology. The goal of this research is not to explain the causes of the changes, but instead to examine the composition and determinants of recent changes in stock price risk.

[6]Source: Avery, Canner, Elliehausen, and Gustafson (1984) Table 8, p. 685 and Bucks, Kennickell, Mach, and Moore (2009) Table 7, p. A27.

markedly through the 1980s and 1990s. These shifts coincide with major demographic trends in the U.S. as baby-boomers started participating in the equity markets. For example, from 1989 to 2008, households who grew up during the Great Depression maintained a relatively low participation rate in equity markets of around 30%. In contrast, baby-boomer equity market participation grew from around 30% to about 60% over the same period.[7]

Undoubtedly, the benefits of broad-based equity ownership would be desirable if they are associated with lower return volatility as a more diffuse set of investors shares the risks (and higher returns) of stock investing. However, some theoretical evidence suggests the exact opposite. Brunnermeier and Sannikov (2009) argue that an expanding financial sector can exacerbate 'endogenous risk' which leads to intermittent periods of high volatility of asset prices. In this paper, we investigate this implication and find that volatility has increased for the stock market as a whole over the period 1964 to 2011. This increase in risk is dynamic with the volatility of stock market volatility increasing through time. Moreover, volatility has increased for individual stocks indicating that high volatility is not just the result of higher correlations among stocks. All told our findings are quite consistent with the 'endogenous risk' theory in so far as an expansion of the stock market appears to have caused significantly more equity volatility. This may be an optimal outcome if the equity investor base desires (and is properly compensated) for the risks it bear. Nonetheless, it is also possible that the existence of a riskier stock market, combined with a lower risk tolerance among young households, will result in a diminished role for equities in household investment portfolios going forward.

Our empirical analysis undertakes a comprehensive examination of equity volatility dynamics of U.S. stocks over the 1964-2011 period. Our main result is apparent in simple sample statistics of sub-periods. But to better understand the specific causes of volatility trends, our detailed analysis utilizes models of price dynamics with time-varying volatility.[8] Our methodology is straightforward

[7]For a detailed discussion of the effects of demographic changes on equity ownership and risk attitudes see Malmendier and Nagel (2011).

[8]The foundation of this literature is the autoregressive conditional heteroskedasticity model of Engle (1982). Subsequent research has developed a large class of models with specific applications to equity price dynamics (e.g., Bollerslev (1986)). Previous empirical studies, including many in the options pricing area, have quite consistently documented that equity prices exhibit time-varying volatility. See, among others, Chernov and Ghysels (2000); Bakshi, Cao, and Chen (1997) and cites therein. Surprisingly, this literature has not examined long-run trends in

but powerful. We utilize a time-series model to decompose firm risk into two components: (i) a long-run volatility component that captures average risk and (ii) a short-run component that measures transitory volatility. We estimate the model for each firm in the U.S. for each year a firm is in our sample. We then examine the trends in estimates of both components as well as the change in the relative importance of each component in the expected volatility of firm returns. We also examine the determinants of each component of volatility in a regression framework.

First, we show that over the last three decades U.S. stocks have indeed become significantly more volatile. This result holds even when excluding the financial crisis period of 2008-2009. After decomposing volatility into a long-run component and a transitory component, we find no meaningful trend in the long-run component of volatility. However, our measure of transitory volatility has tripled over the last 40 years. This evidence is consistent with the findings of Bekaert, Hodrick, and Zhang (2012) that spikes in volatility have become more common. Moreover, we also find that these shocks have become more extreme. Finally, we document that the upward trend in the transitory component is primarily the result of changing firm characteristics associated with the relatively recent appearance of many new firms with riskier fundamentals.

The trend in the transitory component of volatility for the typical firm is sizable. Our estimates show that the transitory component increases from about 20% in 1964 to roughly 60% in 2011. While the change in the transitory component is not strictly monotonic, the recent trough in 2006 is still above the highest estimate before 1985. Our regression analysis reveals important firm characteristics for determining the transitory component. We find that the transitory component decreases with age and liquidity while it increases with growth opportunities, leverage, R&D intensity, and especially with profit volatility. These characteristics are associated with newer firms that have had an increasing tendency to become publicly listed companies over the last thirty years. In fact, the transitory volatility component of new issues increases steadily from the late 1970s through the end of the sample period.

Using a variance decomposition technique, we show that the majority of total volatility can be

volatility dynamics of U.S. firms. Our paper fills this gap by examining trends in equity price risk utilizing results from this conditional heteroskedasticity modeling literature.

attributed to the transitory component with the long-run component of volatility typically being less important. Over the full sample period, the long-run component accounts for 30% of average firm volatility while the transitory component accounts for 70%. However, the split dramatically changes through time as the transitory component becomes a much more important driver of total volatility. We also conduct a detailed attribution analysis for the transitory component and verify that more than half of the time trend can be accounted for by easily observable changes in firm characteristics along with the appearance of newly listed firms in the last few decades. Industry effects and unobserved firm fixed-effects account for about another quarter of the trend. Only about a quarter of the trend in the transitory component is left unexplained by our analysis. This paper also speaks to the apparent contradictory results present in the idiosyncratic volatility literature where the presence of a trend is highly dependent on the sample period examined.[9] The existence of a trend only in the transitory component of volatility explains why previous results have been so sensitive to the sample periods examined.

While our results are evident in simple summary statistics, we also conduct a variety of robustness tests using different time series models. In addition to our primary results which are derived from the GARCH model of Heston and Nandi (2000), we also report results based on the Bollerslev and Mikkelsen (1996) FIEGARCH model and the Engle and Lee (1999) component GARCH model. In unreported results we check that our results are robust to estimation using a variety of other models. In short, the choice of time-series model is not important for our conclusions.

The remainder of the paper is organized as follows. Section 2 presents the motivation for our

[9] Campbell, Lettau, Malkiel, and Xu (2001) document an upward trend in idiosyncratic risk from the 1970s through 1997. Subsequent research attributes this trend to greater growth options, institutional ownership, and competition as well as lower dividends, firm size, and corporate earnings. See, among others, Cao, Simin, and Zhao (2008); Comin and Philippon (2006); Irvine and Pontiff (2009); Wei and Zhang (2006); Xu and Malkiel (2003). Other work suggests that the trend in risk is consistent with an increase in capital market development. Fink, Fink, Grullon, and Weston (2010) find that the trend in idiosyncratic volatility is accounted for by the decrease in the age of firms going public over this period. Similarly, Brown and Kapadia (2007) relate the trend in risk to a 'new listing effect' caused by consistently riskier firms going public from 1975-2000. Moreover, Bartram, Brown, and Stulz (2012) show that equity volatilities of U.S. firms are higher than those of comparable foreign firms and attribute this to better investor protection and equity market development in the U.S. However, other research has questioned the existence of a trend in risk. Brandt, Brav, Graham, and Kumar (2010) claim that a speculative episode, much like that in the 1920s, accounts for a spike in risk in the 1990s that was fully reversed by 2007. Bekaert, Hodrick, and Zhang (2012) examine idiosyncratic risk in 23 global stock markets and find evidence of markets periodically switching into short-lived high volatility regimes, but they find no evidence of an upward trend in volatility.

analysis and results using simple sample statistics. Section 3 describes the data and time-series methodology in more detail. Section 4 presents our detailed results. In Section 5, we examine the robustness of our results. Section 6 concludes.

2. Trends in Volatility

To begin our analysis, we show that trends in risk in the 1964-2011 period are broadly evident in simple sample statistics. We start by calculating a monthly series of standard deviations of daily returns (i.e., volatilities) of the Center for Research on Security Prices (CRSP) Value-weighted Index for the U.S. Panel B of Figure I plots these monthly volatilities along with a simple linear trend line. Visual inspection of the plot reveals an apparent upward trend in volatility. However, it is also clear that a simple linear trend is not well-suited to fitting the dynamics of the monthly volatility process. As has been well-documented, volatility shocks are quite persistent. This is revealed in Figure I as periods of relatively low volatility followed by rapid increases in risk–some of which last for several years. This persistence of volatility suggests that trends in risk could potentially stem from various aspects of volatility dynamics. For example, average levels of risk may trend up because the baseline, or long-run, component of risk increases or because of some combination of more frequent, more extreme, or more persistent volatility spikes. Nevertheless, it is apparent in Figure I that shocks to volatility have become more important over time.

Table I puts specific numbers to the changes in volatility over time by breaking the sample into three sub-periods of equal length. Average (annualized) monthly volatility increases from 10.39% in the 1964-1979 period to 11.85% in the 1980-1995 period and then jumps to 18.08% in the 1996-2011 period. During the financial crisis of 2008, market volatility reached highs not witnessed since the Great Depression. Consequently, we also examine the recent sub-period excluding the months from January 2008 through December 2009. Even without these crisis months, volatility in the 1996-2011 range averages 16.33% which is 38% higher than the 1980-1995 period.

Table I also provides detail on the distribution of monthly volatilities by tabulating the number of months volatilities are above different thresholds. These results show that monthly volatilities are increasing and that extreme volatility events are becoming more common. Specifically, in 122 of the 192 (63.5%) months in the most recent sub-period, volatilities are above the full-sample mean of 13.44%. When we exclude the 24 crisis months, there are still 100 of 168 (59.5%) months with above average volatility in the recent sub-period. To gauge the importance of volatility spikes, we set arbitrary volatility thresholds of 20% and 30% and measure the frequency of months that exceed these values in each sub-period. For the 20% threshold the frequency of exceedances grows over time with the most recent sub-period showing a dramatic increase to 50 of 192 months. In each of the first two sub-periods only one month (0.5%) exceeded the 30% threshold, whereas in the recent sub-period of 192 months, 22 months (11.5%) experienced such high volatility. Both of these findings are robust to excluding the months during the financial crisis. Another way to measure the distribution of volatility is to calculate the standard deviation of monthly volatilities in each sub-period. This "vol-of-vol" measure also increases dramatically over time with the most recent sub-period exhibiting a value more than twice that of the first sub-period. Interestingly, the vol-of-vol appears to increase more steadily than the average volatility. This simple subperiod analysis highlights that spikes in monthly market volatility are getting larger and more frequent.

Determining the statistical significance of the apparent trends in volatility is difficult not only because volatility is persistent but also because this persistence could change over time. Consequently, we defer a detailed discussion of the significance of trends until our subsequent analysis that explicitly accounts for these features. With this caveat in mind, Table II presents results of regression-based estimates of the magnitude of the linear trend in market volatility. The estimated trend of 0.228% represents an economically large increase of more than 10% over the period from 1964 to 2011. We also examine the trend after accounting for the high volatility regimes documented by Bekaert, Hodrick, and Zhang (2012) and continue to find a large trend of 0.146% per year (or 6.9% over the full sample). Stopping the sample period at the end of 2007 (and thus excluding the financial crisis) results in a similar trend estimate.

The apparent trend in market volatility begs the question of whether this finding is due to an increase in the market risk of individual firms or an increase in the correlations among firms (or both). As a first pass at answering this question we collect return data for each firm in the intersection of the Center for Research on Security Prices (CRSP) and CompuStat databases from

1964 to 2011. We restrict our analysis to ordinary shares (share class 10 or 11), shares with a reported price level for each trading day within a given month, and shares with a fraction of zero-trading days less than one-third within a given month.

Figure II presents the equal-weighted average across firms of the volatilities for each month in our sample (Panel A). We also calculate the cross-sectional standard deviation of these volatilities as simple estimates of the dispersion in volatility estimates (Panel B). Each panel is fitted with a linear trend. Panel A shows the now familiar finding of Campbell, Lettau, Malkiel, and Xu (2001) that firm-level volatility increased over the sample period with the predicted cross-sectional mean of volatility increasing two-fold from about 30% in 1964 to over 60% at the end of the sample.[10] As for market risk, this increase is far from monotonic as evidenced by the low volatility period from 2003 to 2006. Such variation in the mean of volatility again raises questions as to the stability of volatility through time. Panel B of Figure II shows that the cross-sectional standard deviation of volatility has more than doubled over the same period from approximately 20% in 1964 to roughly 50% in 2011, yet this statistic also exhibits substantially higher frequency variation. These results suggest that market risk is increasing, at least in part, because of increases in firm-level risk.

The sample of publicly-traded firms has changed substantially over time (Brown and Kapadia, 2007), so it may be important to disentangle trends in the average transitory component of volatility at the firm level from a purely cross-sectional composition phenomenon. As a first pass, we form a panel of firm-year observations of two naïve volatility estimates. We define the Naïve Volatility as the sample average of the monthly annualized standard deviations of daily returns and the Naïve Transitory Component as the sample standard deviation of the monthly annualized standard deviations of daily returns over rolling five-year windows.[11]

Estimates of the trends in these series are presented in Table III. We begin by estimating a linear trend on the cross-sectional means of both the Naïve Volatility and the Naïve Transitory Component. Both series have statistically significant and positive trends. The predicted cross-

[10]While most other papers examining the trend in firm risk examine idiosyncratic volatility, we focus on total risk. Because most risk at the individual stock level is idiosyncratic, the findings are similar for total risk and various measures of idiosyncratic risk.

[11]To be included, a firm must trade each month in the center year.

sectional mean of Naïve Volatility increases approximately 0.7% per year from 31% in 1964 to 64% in 2009 and the predicted cross-sectional mean of the Naïve Transitory Component increases approximately 0.5% per year from roughly 20% in 1964 to 51% in 2009.

We also estimate the trend models in the full panel controlling for changes in sample composition through firm-level fixed effects. After controlling for firm characteristics, the Naïve Mean of Volatility exhibits no trend across the sample period. However, the Naïve Transitory Component continues to exhibit a large positive and statistically significant time trend. In Table III, Panels B and C, we also report results from estimating trends that account for the volatility regimes estimated by Bekaert, Hodrick, and Zhang (2012) and that exclude the recent financial crisis period. In these cases, the between estimates for the Naïve Volatility and Naïve Transitory Component are both positive and significant. However, once we account for firm-level fixed effects, the Naïve Volatility trend is significantly negative while the Naïve Transitory Component remains positive and significant. These model-free results are our first hint that the differences between the trends of long-run volatility and transitory volatility depend importantly on firm characteristics.

The naïve metrics, however, do not allow us to satisfactorily disentangle the dynamics of each series through time. In fact, the series are highly correlated with each other (Pearson correlation coefficient of 0.85). Consequently, we must utilize more sophisticated methods for obtaining independent and reliable estimates of both average volatility and the transitory component. To this end, we now turn to estimating a structural random volatility process that allows for the joint estimation of both a constant (long-run) component and a transitory component of volatility for a given firm.

3. Methodology

To mirror our panel of firm-year naïve estimates of volatility, we estimate the GARCH model of Heston and Nandi (2000) for each firm in the intersection of the CRSP and CompuStat universes over rolling five year windows. A firm must have a daily observation for all trading days in the center year of the window (no more than one-third of which are zero returns). After restricting our analysis to ordinary shares, we obtain a total of 126,039 firm-years of daily return data. For each of these series, we then estimate the following Heston-Nandi GARCH (HNGARCH) model

$$\log S_t = \log S_{t-1} + r + \lambda h_t + \sqrt{h_t} z_t \tag{1}$$

$$h_t = \omega + \beta h_{t-1} + \alpha(z_{t-1} - \gamma\sqrt{h_{t-1}})^2 \tag{2}$$

where S_t is the stock price at date t, r is the continuously compounded risk-free rate of return which we define as the natural logarithm of one plus the one-month Treasury bill rate, h_t is the variance of the stock price at date t, and z_t is a standard normal random variable. The parameters of the model are: λ, a GARCH-in-mean type loading on contemporaneous variance, ω, the long-run component of variance, α, the volatility of volatility, β, the GARCH parameter which measures the persistence in variance, and γ, a skewness parameter. We estimate this model using maximum likelihood with the following restrictions: $\omega > 0$, $\alpha > 0$, $1 > \beta > 0$, and $1 > \beta + \alpha\gamma^2$. The first two restrictions require that the constant and transitory components are positive while the second pair of restrictions guarantees a finite variance.[12] We estimate the model using daily returns for each firm in our sample each year. Depending on the application of the model we use either one year of non-overlapping returns or (up to) five years of overlapping returns.

From these parameter estimates, we define three measures to help assess the overall fit of our model. We also generate an additional three measures that we utilize in our subsequent analysis.[13] The Mean Squared Error is simply the mean squared error from the mean equation (1). The Mean of Predicted Volatility is the sample average of the predicted annualized volatilities. The Volatility of Predicted Volatility is the sample standard deviation of the predicted annualized volatilities.

[12] The initial variance, h_0, is set equal to the sample variance of the log returns in excess of the risk-free rate. To help ensure the maximum is not local, we repeat the entire estimation using ten sets of randomly selected starting values and using one set of parameters with $\lambda = 0.5$, $\gamma = 0$, and the remaining parameters set equal to the estimates from a standard GARCH(1,1) model. The set of parameters with the maximum log likelihood among these eleven estimates is then selected for each firm-year.

[13] We have also explored an additional Mean-reversion Component of volatility, defined as $1 - \beta - \alpha\gamma^2$, which captures changes in the persistence of volatility shocks through time. Decomposing the time-series variation in the natural logarithm of Mean of Volatility within a given firm, we find that on average 91.80% of the variation in the natural logarithm of the Mean of Volatility is explained by variation in the natural logarithm of the numerator, $(\omega + \alpha)$. Moreover, the remainder of our analysis is qualitatively similar. Thus, we focus on the two components of volatility defined in equations (4)–(5); results tabulated with the additional Mean-reversion Component are available from the authors by request.

The variables used in our later analysis are defined as follows:

$$\text{Mean of Volatility} = \sqrt{252 \cdot (\omega + \alpha)/(1 - \beta - \alpha\gamma^2)} \tag{3}$$

$$\text{Long-run Component} = \sqrt{252 \cdot \omega/(1 - \beta - \alpha\gamma^2)} \tag{4}$$

$$\text{Transitory Component} = \sqrt{252 \cdot \alpha/(1 - \beta - \alpha\gamma^2)} \tag{5}$$

These variables let us disentangle the constant component of volatility (which we call the Long-run Component for expositional purposes) from the time-varying component of volatility (which we simply call the Transitory Component). We have annualized our estimates to facilitate comparison with our naïve metrics. Our final sample consists of estimates for 126,014 firm-years.[14]

Table IV presents the Pearson correlation coefficients between our naïve volatility estimates, our model specification measures, the Mean of Volatility and our components of volatility. All three of our metrics for average volatility, Mean Squared Error, Mean of Predicted Volatility and Mean of Volatility, are highly correlated with our Naïve Volatility. This indicates that the Mean of Volatility calculated from the GARCH estimation matches well with the Naïve Volatility observed in the previous section. Similarly, our model-based metric of the transitory component correlates well with our naïve components (Pearson correlations of 0.911 and 0.882). Importantly, we also observe a much lower level of correlation between the Long-run Component and the Transitory Component estimates from the HNGARCH model (when compared to the correlation between our naïve metrics designed to capture the same effects). The correlation of 0.038 between the HNGARCH estimates relative to the roughly 0.851 between naïve estimates indicates that our joint estimation procedure is successful in disentangling the covariation between the two series.[15]

[14] A very small number of our estimates (0.02%) have an absolute difference in Mean of Volatility and Mean Squared Error scaled by Mean Squared Error that exceeds 100%. We exclude these firm-year observations from our sample as possible convergence issues.

[15] Somewhat surprising is the higher correlation between the Transitory Component and the measures of the central tendencies of volatility from both the GARCH estimation and our naïve estimates relative to the correlation between the Long-run Component and these same measures of central tendencies. Most notably the correlation between the Transitory Component and the Mean of Volatility is 0.928 whereas the correlation between the Long-run Component and the Mean of Volatility is only 0.385. This hints at the importance of dynamics of realized innovations and their amplification through the Transitory Component in the determination of the observed volatility series in a given firm-year.

In the next section, we present our main results concerning trends in the individual components of the Mean of Volatility. We also examine the firm characteristics that help determine both cross-sectional and time-series variation in these components. Our independent variables in these panel regressions are defined as follows: We assume a linear trend variable equal to the year of the firm observation less the first year of our sample, 1964. The Amihud Ratio for a given firm-year is defined as in Amihud (2002) and Hasbrouck (2009) as

$$\text{Amihud Ratio} = 10^6 \cdot \frac{1}{T} \sum_{t=1}^{T} |\log \frac{S_{i,t}}{S_{i,t-1}}| \ / \ |S_{i,t} \cdot Vol_{i,t}| \tag{6}$$

where $S_{i,t}$ is the price level and $Vol_{i,t}$ is the total number of shares traded of firm i at date t both from CRSP and T is the length of the return series for a given firm-year. Log Amihud Ratio is the natural logarithm of one plus the Amihud Ratio. Log Size is the natural logarithm of one plus the market capitalization from CRSP as of year-end for a given firm-year adjusted for inflation. Book-to-Market Ratio is the ratio of the book value of equity from the CompuStat annual database and market capitalization from CRSP winsorized at the 1^{st} and 99^{th} percentiles. Book value of equity is equal to the shareholder's equity (SEQ) or the sum of common equity (CEQ) and preferred stock (PSTKRV) or total assets (AT) minus liabilities (LT). Log Profit Volatility is equal to the natural logarithm of the five-year centered standard deviation of the ratio operating income before depreciation to sales from the Compustat Annual database where profit volatility is constrained to be less than 100%. R&D Share is equal to research and development expense (XRD) divided by the sum of capital expenditures (CAPX) and research and development expense from the CompuStat annual database. If a firm had neither research and development expenses nor capital expenditures in a given year, R&D Share is set equal to zero. Leverage is defined as the sum of current liabilities (LCT), long-term debt (DLTT), and preferred stock less cash and short-term investment (CHE) from the CompuStat annual database. This value is scaled by total assets and winsorized at the 99^{th} percentile. Listing year is defined as the minimum of (i) year of listing date from Jovanovic and Rousseau (2001), (ii) year of issue date from Field and Karpoff (2002) and Loughran and Ritter (2004), and (iii) the year of the firm's initial appearance in the CRSP monthly database.

Listing Groups are a series of indicator variables which take the value one when the listing year is between the stated date range and zero otherwise. Log Age is equal to the natural logarithm of one plus the year of the observation minus the listing year. We also utilize the French 17 Industry classification.[16]

4. Results

4.1. Trends in the components of volatility

We begin our main results by analyzing the trends in the components of volatility. Figure III plots the cross-sectional means of the components of volatility through time along with their predicted values from a linear trend model. Table V presents the cross-sectional summary statistics of the time-series medians of a given firm's volatility components for five subsamples, 1964-1969, 1970-1979, 1980-1989, 1990-1999, and 2000-2011, as well as the full sample. Table VI presents the estimated coefficients from this "between estimation" along with the robust *p*-values.

Table V shows that the mean Long-run Component exhibits an increase from the pre-1980 period through 1999 after which it declines significantly. There is no trend in the median values of the Long-run Component. In contrast, both the mean and median Transitory Component show monotonic upward trends over the entire sample period. Taken together, the graphical evidence in Figure III and the volatility estimates provided in Table V are strongly suggestive of a considerable upward trend in the Transitory Component but little, if any, trend in the Long-run Component.

Another interesting feature in these estimates is the lack of a role for the Long-run Component during the financial crisis of 2008 compared to its peak during the burst of the dot-com bubble. Based on the graphical evidence in Figure III, we see uncertainty consistent with that described by Pástor and Veronesi (2006) in both the Long-run Component and the Transitory Component in the late 1990s. However, during the financial crisis, much of the peak in the Cross-sectional Mean of Volatility observed in Figure I is driven by an increase in the Transitory Component coupled with a sizable decrease in the Long-run Component. This evidence is consistent with the very volatile

[16] We thank Ken French for making these data available on his website.

behavior of the S&P 500 Volatility Index (VIX) observed over this time period. The VIX rose from a low of 16.3 on May 16, 200,8 to a high of 81.5 on November 20, 2008.

To estimate the magnitude of a linear trend and its statistical significance, we repeat the analysis conducted for Table III using our HNGARCH-based estimates. Results in Table VI reveal a statistically significant and positive trend in both the Long-run and Transitory Components. The between estimate of the trend in the Long-run Component of 0.122% per year is much lower than the between estimate of the trend in the Naïve Mean of Volatility of 0.711% (reported in Table III). However, the magnitude of the trend in the Transitory Component is greater than that observed in the Naïve Transitory Component with the predicted value trending upward at a rate of about 0.8% per year, or from approximately 22% to 59% over the 47 year sample.

Values reported in Table VI reveal that the trend in the Long-run Component reverses sign when estimated in the panel with firm-level fixed effects. This negative trend implies that simply controlling for firm-specific characteristics and changes in the sample composition through time undoes the trend in volatility brought to light in Campbell, Lettau, Malkiel, and Xu (2001). In contrast, the upward trend in the Transitory Component is present even after controlling for firm-level effects, though it is reduced in magnitude. Intuitively, an upward trend in the Transitory Component would lead to increasingly large deviations from the Long-run component of volatility through time reinforcing the diminished role of the Long-run Component. Results provided in Panels B and C show that these trend results are robust to controlling for the high-volatility regimes of Bekaert, Hodrick, and Zhang (2012) as well as excluding the financial crisis (as in Brandt, Brav, Graham, and Kumar (2010)).

4.2. Within-firm volatility dynamics

Our methodology allows for determining the relative importance of the components of volatility for the firms in our sample. Specifically, we determine the within-firm Mean of Volatility through the following variance decomposition:

$$1 = \frac{\mathrm{Cov}(\frac{\omega}{1-\beta-\alpha\gamma^2}, \frac{\omega+\alpha}{1-\beta-\alpha\gamma^2})}{\mathrm{Var}(\frac{\omega+\alpha}{1-\beta-\alpha\gamma^2})} + \frac{\mathrm{Cov}(\frac{\alpha}{1-\beta-\alpha\gamma^2}, \frac{\omega+\alpha}{1-\beta-\alpha\gamma^2})}{\mathrm{Var}(\frac{\omega+\alpha}{1-\beta-\alpha\gamma^2})} \tag{7}$$

The first term on the righthand side of the equation is a measure of the contribution to total risk from the Long-run Component and the second term is a measure of the contribution from the Transitory Component. By construction, these two values sum to one so they can be interpreted as the relative proportion of volatility attributable to these two components. To avoid the unknown serial correlation structures in the components of volatility induced by a rolling window estimation, we examine components of volatility estimated using a single year of returns. We calculate the variance decomposition for each firm with at least six years of data and then take the mean and median across firms. Table VII reports the results of this component analysis. For both the mean and median, we observe a decrease in the importance of the Long-run Component through time. In the 1960s the Long-run Component was responsible for about half of total risk, but in the most recent period this share had fallen to only a quarter of total risk. In other words, the covariance between the Transitory Component and the Mean of Volatility has had an increasing role in determining the total variance for a given firm. Even within the full sample, variation in the Transitory Component explains over 70 percent of the variation in the Mean of Volatility. This again lends credence to investigating these components of volatility separately.

4.3. Determinants of volatility dynamics

We now turn to trying to understand what firm characteristics have led to the substantial increase in the Transitory Component of volatility. As a first pass, we examine the time-series median of a firm's volatility components (as defined above) sorted by the firm's characteristics. For each firm with at least six observations, we calculate the time-series median of the firm's Book-to-Market Ratio, Size, Profit Volatility, R&D Share, Leverage and Amihud Ratio. Amihud Ratio is demeaned in each year to adjust for time-varying liquidity in the aggregate market. Using these firm medians, we then rank each firm into quintiles with firms in quintile one having the lowest Book-to-Market Ratio, the smallest size, or the most liquid shares (depending on the firm characteristic). We also examine IPO vintage by sorting firms into listing groups: pre-1970, 1970-1979, 1980-1989, 1990-1999, and 2000-20011. We study firm age by forming four age groups: 1-4 years, 5-10 years 11-20 years and more than 20 years.

Table VIII presents the summary statistics of the volatility estimates for each firm characteristic. These univariate results provide an indication of the important determinants of volatility ignoring within-firm variation in characteristics through time. We observe that small size, low Book-to-Market, high profit volatility, high R&D share, and young firms are associated with a higher Long-run Component. With the exception of the effect of the Book-to-Market ratio, these same patterns emerge for the Transitory Component. Extreme illiquidity plays a large role in the Transitory Component as evidenced by the average 90% annualized transitory component in the highest quintile of the Amihud Ratio. We also observe the listing group effect of Brown and Kapadia (2007) in the increase of both Long-run Component and the Transitory Component through 1999 though both decline in the most recent sub-period. Together these results suggest that firm characteristics are quite important for determining overall risk. Since many of these characteristics also have time-series trends at the firm level and in aggregate, it is likely that trends in volatility are related to trends in firm charatceristics.

While the evidence provided in Table VIII is suggestive of factors that are important for explaining the trend in volatility, many of these factors are correlated. In addition, it is interesting to determine if these factors are sufficient for explaining observed trends. Consequently, we now turn our attention to exploring the cross-sectional and time-series determinants of volatility with the explicit purpose of testing whether the dynamics of each of the firm-specific characteristics explain the patterns in volatility. To this end, we perform separate panel regressions for the Long-run and Transitory Components of Volatility. We include in our analysis the explanatory variables defined above as well as industry-level fixed effects. To calculate statistical significance we use robust standard errors corrected for clustering at the firm level. Table IX presents the estimated coefficients from these regressions along with marginal effects calculated using a perturbation of one standard deviation in the independent variable. We present panel regressions using non-overlapping five-year periods from 1967 to 2011. The independent variables in these regressions are equal to the mean value of the specific firm-characteristic over the five-year window.[17]

The results in Table IX show that many factors are important determinants of both the Long-

[17]Specifically, we use the estimated volatility components from 1969, 1974, and so on, up to 2009. Independent variables are equal to the mean value over the 1967 to 1971 window, the 1972 to 1976 window, and so on, up to the 2007 to 2011 window.

run Component and the Transitory Component. We start by analyzing the results for the Long-run Component. Unlike the firm-level fixed effects estimation in Table VI, we fail to identify a significant time trend in the Long-run Component after controlling for observed firm and industry characteristics. Consistent with Pástor and Veronesi (2003), we find that smaller and younger firms, as well as firms with more uncertainty surrounding their profits (as measured by profit volatility, (Wei and Zhang, 2006)), have higher long-run volatility. A larger R&D Share and a lower Book-to-Market ratio are also positively related to long-run risk. These effects are consistent with the measures serving as a proxy for growth opportunities as in Cao, Simin, and Zhao (2008). The marginal effects (MFX) show that many of the effects are economically large as well as statistically significant. The most important determinants of the Long-run Component are firm size, age, and R&D share.

The coefficients on listing groups allow us to examine the 'new listing effect' of Brown and Kapadia (2007) in which increasingly risky firms went public over the 1980s and 1990s. Surprisingly, an increase in riskiness by listing group is not evident in the Long-run Component. Instead, the Long-run Component of new issues decreases monotonically over our sample. In fact, firms listed in the 2005-2011 period show the lowest Long-run Component of any listing group after controlling for other factors. These effects differ from the univariate results in Table VI indicating that at least some of the differences in firms that have gone public through time are captured in the other firm-specific controls that we include.

As suggested by the previous findings, the results for the Transitory Component are strikingly different. First, we find that the Transitory Component increases through time even after accounting for many firm-specific factors and industry effects. The value of 0.39% per year suggests that the Transitory Component has increased by about 18% over the 1964-2011 period for reasons not related to the firm-specific and industry effects for which we account. Comparing this trend estimate to those provided in Panel A of Table VI allows us to approximate the general determinants of the trend in the Transitory Component. The results suggest that about half of the trend in the Transitory Component is accounted for by the firm and industry characteristics we examine. About another quarter of the trend is accounted for by some unknown set of fixed firm-specific characteristics that we do not include in our analysis. Implicitly, the remaining quarter of the trend must be due to unmodeled time-varying characteristics (e.g., a mix of time-varying firm, industry, and market factors). In the next section we undertake a more detailed attribution analysis.

Turning to the firm-specific factors that determine the Transitory Component we observe both similarities and differences from the results for the Long-run Component. One important difference is for the Amihud measure of liquidity. Whereas there was a weak positive relation between illiquidity and the Long-run Component, we find a very large and significant positive relation between illiquidity and the Transitory Component. Surprisingly, there is no significant relation between firm Book-to-Market and the Transitory Component; in other words, value stocks tend to have a similar transitory volatility as their growth stock counterparts. Profit volatility, R&D share, and leverage are all positively related to the Transitory Component, and firm age has a negative relation. Each of these findings is similar to those for the Long-run Component (except that leverage is only statistically significant in the Transitory Component estimation). The negative coefficients for firm age suggest that at least part of the uncertainty for both the Long-run Component and the Transitory Component is resolved as firms mature. This evidence is consistent with Loughran and Ritter (2004) in which firm age at listing increased after the dot-com bubble burst relative to the younger IPOs seen in the 1980s and 1990s. Nonetheless, the marginal effects for the Transitory Component show that the economic significance of liquidity and profit volatility dwarf the importance of the other factors.

Examining the estimated coefficients on the listing group dummy variables reveals a much different pattern for the Transitory Component than for the Long-run Component. The Transitory Component started to increase significantly with the 1975-1984 listing group. Each of the coefficients from the 1975-1984 group through the 2005-2011 group are statistically different from the pre-1965 listings. Moreover, these estimates are monotonically increasing in listing group. These results suggest that the new listing effect documented by Brown and Kapadia (2007) is entirely due to an increase in the Transitory Component as opposed to an increase in the Long-run Component.

One way to gain intuition about the results in Table IX is to consider the determinants of the Long-run Component as primarily determining the overall level of volatility and the determinants of the Transitory Component as determining the amount of tail risk. In cases where the coefficients on factors are the same sign, the effect of a change in the factor will compound total risk. In cases where the signs are opposite, a change in the factor will have, to some degree, offsetting effects on the Long-run Component and the Transitory Component. With this in mind, we see that differences (and changes) in profit volatility, R&D share, and age are associated with compounding risks. For example, higher profit volatility not only shifts the mean of volatility up but also shifts density in the distribution of volatility to the tails. Finally, it is interesting to note that the factors we consider are drastically better at explaining the variation in the Transitory Component than the variation in the Long-run Component. The adjusted R-squared of the Transitory Component estimation is 0.512 as opposed to only 0.161 for the Long-run Component estimation.

4.4. Attributes of the trend in Transitory Volatility

The trend in the Transitory Component can be thought of as arising from three sources: changes in sensitivities to firm characteristics through time (time-varying sensitivities), changes in sample composition and characteristics through time (time-varying means) and unexplained changes captured by the time trend variable. Figure IV plots three different series that show the relative importance of these sources of variation. The first series (dashed line) is evaluated at the full-sample means and full-sample sensitivities but allows for variation through the estimated time trend. This represents the part of the trend we cannot explain. The second series (red line) is constructed at the full-sample sensitivities presented in Table IX and time-varying means of the independent variables. The difference between this line and the dashed line shows that a large part of the variation in the Transitory Component is explained by changes in firm characteristics (including changes due to the addition of new firms and loss of old firms).

The third series in Figure IV (dark line) is evaluated at time-varying sensitivities estimated in yearly cross-sectional regressions and the time-varying means of the independent variables. The difference between this line and the red line shows that higher-frequency variation in the Transitory Component, but very little of the trend in the Transitory Component, is accounted for by time varying sensitivities. Moreover, this plot suggests that time-varying sensitivities of the Transitory Component to firm characteristics comprise very little of the variation in the Transitory Component over the early three-quarters of our sample. The black line begins diverging from the red line in the late 1990s. This is consistent with trends discussed in the introduction as well as with possible changes in the marginal investor. For example, the late 1990s saw an increase in the number of retail investors and the shift from defined benefit retirement plans to self-directed defined contribution plans documented in Brandt, Brav, Graham, and Kumar (2010). However, the linear time trend and changes in the sample composition account for roughly 80 percent of the total observed variation in the aggregate Transitory Component.

In order to quantify these three sources of variation, we decompose the change in the predicted Transitory Component from 1969 to 2009 (the center years of our first [1967-1971] and last [2007-2011] non-overlapping five-year periods) by noting the following:

$$\bar{X}_1\hat{\beta}_1 - \bar{X}_0\hat{\beta}_0 = (\bar{X}_1 - \bar{X}_0)\hat{\beta}_{FS} + \bar{X}_1(\hat{\beta}_1 - \hat{\beta}_{FS}) + \bar{X}_0(\hat{\beta}_{FS} - \hat{\beta}_0) \tag{8}$$

where $\hat{\beta}_{FS}$ is the vector of full sample sensitivities reported in Table IX, $\hat{\beta}_0$ is the vector of sensitivities in 1969, $\hat{\beta}_1$ is the vector of sensitivities in 2009, $\bar{X}_0$ is the vector of means in 1969 and $\bar{X}_1$ is the vector of means in 2009.[18] The first term of the right-hand side of equation (8) captures the change in the predicted Transitory Component due to changes in sample composition while the remaining two terms are the change attributable to changes in sensitivities to firm characteristics through time. The difference between the intercepts in the two cross-sectional regressions is then the unexplained time trend.

Table X reports the results of this attribution analysis. Over our sample period, the cross-sectional mean of the Transitory Component increases 31% from 29 percent in 1969 to 60 percent in 2009. Approximately 60 percent of this change can be attributed to changes in the sample composition and changes in the sensitivities of the Transitory Component to firm characteristics included in our analysis. Much of this explained change is concentrated in the listing group effects of Brown and Kapadia (2007) which captures changes in the fundamental risks of companies going

[18] Parameters that are not identified in the cross-sectional regressions such as the listing group effects in the 1969 regression are set to zero.

public through time. Positive contributions come from both the listing groups themselves (tabled in the 'Change in Means' column) and the changes in sensitivities. All together listing vintage alone accounts for about 25% of the total trend in the Transitory Component. Of course, the firm characteristics we study also change with listing group so the total variation attributable to new firms is likely to be even larger.

As suspected, firm characteristics also play an important role in the trend of the Transitory Component. Changes in the Transitory Component due to changes in sample firm characteristics through time are driven primarily by firms with riskier cash flows and more illiquid firms. Higher aggregate profit volatility is consistent with an increase in equity market development, i.e., riskier firms having increasing access to public equity markets through time. The Transitory Component is also less sensitive to cash flow risk in the early sample which may stem from changes to disclosure regulation over time or the ease of earnings manipulation. Later in the sample, the prevalence of less levered firms and firms with higher R&D share also contribute to these compositional effects but to a lesser extent. Interestingly, total changes to the trend attributable to size is quite negative even though there has been a significant increase in the number of small firms. Some of this variation may be better captured by firm age which is the second most important firm characteristic for explaining the trend in the Transitory Component.

The industrial composition of the sample plays only a small role in the observed trend in the transitory component. These changes are primarily focused in the sensitivity to firms classified as utilities, an industry which underwent changes in riskiness due to deregulation, and those classified in the catch-all 'Other' category, which has no doubt changed with the shift to a more service-based economy.

Overall, we see that many factors (including unobserved ones) are related to the significant upward trend in the Transitory Component. A large part of the trend is related to firms listing after 1980 which have tended to be smaller, younger, more R&D intensive, and have higher profit volatility.

5. Additional Tests

We conduct some additional tests to gauge the robustness of our results. First, we consider our results in the context of alternative GARCH models, which allow for more flexibility in conditional volatility. Next, we estimate a pooled GARCH model that allows us to simultaneously estimate the trends in volatility components and the effects of firm characteristics on volatility.

5.1. Results using alternative GARCH models

Despite the consistency of our results across both naïve measures and measures derived from the HNGARCH model, a potential concern with our findings is their dependence on the specific GARCH model used. In this section, we show that similar quantitative results are obtained using either of two alternative GARCH models: the component GARCH model of Engle and Lee (1999) and the fractionally integrated EGARCH (FIEGARCH) model of Bollerslev and Mikkelsen (1996).

5.1.1. Engle and Lee (1999) component GARCH model

Our analysis closely relates to the component GARCH model of Engle and Lee (1999) in that both models decompose volatility into a long- and short-run (transitory) volatility component. Specifically, the Engle and Lee (1999) component GARCH model is given by:

$$r_t - r = \sqrt{h_t} z_t = \varepsilon_t \tag{9}$$

$$h_t = q_t + s_t \tag{10}$$

$$s_t = (\alpha + \beta) s_{t-1} + \alpha(\varepsilon_{t-1}^2 - h_{t-1}) \tag{11}$$

$$q_t = \omega + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - h_{t-1}) \tag{12}$$

where r_t is the stock return at date t, r is the continuously compounded risk-free rate of return which we define as the natural logarithm of one plus the one-month Treasury bill rate, h_t is the variance of the stock price at date t, and z_t is a standard normal random variable. h_t is the sum of the two volatility components: q_t the long-run component, which is always positive, and s_t the transitory component, which can be positive or negative.[19]

In order to identify the transitory component of volatility, the component GARCH model fixes the expected value of the transitory component to zero. Moreover, this model allows for negative values of s_t; that is the transitory component can serve to adjust the long-run component up or down. We therefore define three firm-year measures in order to assess the change in the relative importance of the transitory component in determining expected volatility over our sample. The Standard Deviation of s is the standard deviation of the annualized value of s_t taken over the estimation window. The Persistence of s is the sum of α and β. s Share is the mean of $\frac{|s_t|}{q_t+|s_t|}$ taken over the estimation window. When scaled by 100, this final measure captures the fraction of total volatility attributable to the transitory component of volatility.

The first three columns of Table XI report the results of fitting a linear trend on these three measures. First, we document a significant increase in the Standard Deviation of s over our sample both for the average firm and after accounting for changes in sample composition over our sample period. During the past 47 years, the transitory component of volatility has become more disperse. This dispersion manifests itself in large deviations of volatility from the expected volatility based solely on the long-run component. Persistence of s has also increased over our sample. For the average firm, the half-life of the transitory component of volatility has increased by more than 50% (from 1.02 to 1.63) over the past 47 years. Finally, we observe that the fraction of total volatility attributable to the transitory component of volatility has increased significantly over our sample period. Over the full sample, we estimate an increase in s Share of 8.32% for the average firm in our sample, which is consistent with the transitory component playing a more substantial role in determining expected volatility in more recent years. As before, this increase is not purely a sample composition effect but is also observable at a similar magnitude within individual firms.

[19] As before, we estimate this model for each firm over rolling five year windows. Engle and Lee (1999) give conditions for the stationarity of this model. Specifically, we require that $1 > \rho > (\alpha + \beta) > 0$, $\beta > \phi > 0$, $\alpha > 0$ and $\omega > 0$.

5.1.2. Bollerslev and Mikkelsen (1996) FIEGARCH model

Despite the introduction of two volatility components with different decay rates in the above model, empirical evidence suggests that sample autocorrelation functions deviate substantially from theoretical decay rates.[20] Thus an alternative class of models specify volatility as a fractionally integrated process with 'long memory.' These models allow for longer lived persistence in shocks to volatility, which falling between a stationary process, as in the previous models explored in this paper, and an unit root process where shocks to volatility are infinitely persistent.

In this subsection, we recast our results in the framework of the fractionally integrated EGARCH model of Bollerslev and Mikkelsen (1996). These results, while quantitatively similar to our other results, help alleviate several concerns regarding our earlier specifications. Namely, the FIEGARCH model is less restrictive regarding the persistence of shocks to volatility and allows for partial integration of the volatility series. The EGARCH model expresses volatility under a log transformation such that conditional variance is always positive and the parameters governing the process need not be restricted during estimation. Finally, we estimate the FIEGARCH model with shocks to the return process that are distributed under the Generalized Error Distribution. This distributional assumption allows for excess kurtosis and reduces the impact of extreme returns on the volatility series.

Specifically, the FIEGARCH model is given by:

$$r_t - r = \sqrt{h_t} z_t, \quad z_t \sim GED(\nu) \tag{13}$$

$$\ln(h_t) = \omega + \phi(L)^{-1}(1-L)^{-d}[1+\psi(L)]g(z_{t-1}) \tag{14}$$

$$g(z_t) = \theta z_t + \gamma[|z_t| - \mathrm{E}(|z_t|)] \tag{15}$$

where r_t is the stock return at date t, r is the continuously compounded risk-free rate of return which we define as the natural logarithm of one plus the one-month Treasury bill rate, h_t is the variance of the stock price at date t, and z_t is a Generalized Error Distribution random variable

[20]See for example Ding, Granger, and Engle (1993) and Bollerslev and Mikkelsen (1996), among others.

with scaling parameter, ν.[21] In this model, $\ln(h_t)$ follows an ARFIMA(1,d,1) process rather than an ARMA(1,1) process as in Nelson (1991).[22]

While results are not directly comparable to the other models that we estimate, we define three measures that allow us to evaluate our previous results in this FIEGARCH framework. Mean of h_t is the sample average of the predicted annualized volatilites from our FIEGARCH estimates winsorized at the 99^{th} percentile.[23] This measure is similar to the Long-run Component from the HNGARCH model and captures the expected value of long-run volatility. Similarly, Vol of h_t is the sample standard deviation of the predicted annualized volatilities from the FIEGARCH estimates winsorized at the 99^{th} percentile. This measure pairs with the Transitory Component from our HNGARCH estimates and the Std Dev of s measure from the component GARCH model in that it captures the extent to which volatility deviates from its long-run mean. Finally, d is the estimated fractional integration term. This term is similar to the Persistence of s measure from our component GARCH estimations in that it governs the decay rate of a shock to the volatility system. As d increases, the process has longer memory and innovations in volatility have a longer half-life.

The last three columns of Table XI report the results of fitting a linear trend on these three FIEGARCH measures. Consistent with both the results using naïve estimates presented in Table I and the results using HNGARCH estimates presented in Table IV, we find that Mean of h_t has increased over our sample period. However, this increase is driven by compositional effects as in Brown and Kapadia (2007). After controlling for firm-level fixed-effects, we find a decrease in the Mean of h_t of 0.22% per year which is almost identical to the estimated trend in the Long-run Component of the HNGARCH model. Turning to Vol of h_t, we find that vol-of-vol has increased over our sample both due to changes in the average firm (compositional effects) and changes in risk within firms through time. We estimate that Vol of h_t has increased almost 21% over our

[21] See Nelson (1991) for additional information about the Generalized Error Distribution.

[22] As before, we estimate this model for each firm over rolling five year windows. We truncate the moving average representation of the volatility process at the minimum of the return series length and 1000. We exclude 14.3% of the 188,840 firm-year estimates in which we have convergence due to non-stationary volatility processes ($d \geq 1$) or over-differenced volatility processes ($d < 0$). Estimation is carried out using the G@RCH package in OxMetrics. Additional estimation details can be found in Bollerslev and Mikkelsen (1996) and Laurent and Peters (2002).

[23] Since the restriction that volatility is positive naturally skews its distribution, we also consider the Median of h_t in unreported results. Trend esimates are quantitatively similar to those for the Mean of h_t and are available from the authors upon request.

sample with approximately 10% of this change coming from an increase in risk within firms. Much of this increase in within firm risk comes towards the end of our sample and specifically during the financial crisis as evidenced by the lack of a significant trend after controlling for the high variance regimes of Bekaert, Hodrick, and Zhang (2012) or dropping the financial crisis from our sample. This increase in the vol-of-vol seems to be linked to an increase in the persistence of innovations to the volatility process as d increases over our sample period both for the average firm and after controlling for firm-level fixed-effects. These results mirror the results from the component GARCH measures where the Std Dev of s and the Persistence of s increased over our sample period.

In summary, our primary findings hold regardless of the specification of volatility that we choose. Over the last 40 years, firm risk has increased both for the average firm and for individual firms on average. This increase in riskiness, however, is not one dimensional. In our tests, we find that the long-run mean of volatility has decreased, but this reduction in the level of risk is offset by an increase in the volatility of volatility. Firm volatility varies more through time towards the end of our sample as innovations in the volatility process linger in the system longer and drive the persistence of volatility away from its long-run mean.

5.2. Pooled estimation

Changes in firm characteristics over the 5-year estimation window could drive changes in the volatility of a firm's returns that are picked up in an increased Transitory Component term rather than the Long-run Component term. To address these potential biases in our estimation, we perform a pooled HNGARCH estimation using quarterly returns. This approach allows us to define the volatility parameters ($\omega_{i,t},\ \alpha_{i,t},\ \beta_{i,t}$) in equation (2) as a function of the characteristics of firm i in quarter t denoted as the vector $X_{i,t}$ below. In order to maintain the model restrictions, we transform the volatility parameters as follows:

$$\omega_{i,t} = \exp\{X_{i,t}\ \delta_1\} \tag{16}$$

$$\alpha_{i,t} = \exp\{X_{i,t}\ \delta_2\} \tag{17}$$

$$\beta_{i,t} = \text{logit}^{-1}\{X_{i,t}\ \delta_3\} = 1/(1 + \exp\{-X_{i,t}\ \delta_3\}) \tag{18}$$

Due to the nonlinearities of this model, we report the marginal effects of a change of one standard deviation, in the case of continuous variables, in the independent variable on the Mean of Volatility given in equation (3). For the trend and discrete variables, we compute a perturbation of one year and from a value of 0 to a value of 1 for all observations respectively. All other controls are evaluated at the cross-sectional mean values.

Table XII reports the results of this pooled estimation. Even after controlling for aggregate changes in firm characteristics over the sample period, we observe a predicted change in the annual Mean of Volatility from 28.9% in 1964 to 49.7% in 2011 holding all other variables at their mean values. This result, which is driven solely by the estimated trends in the components of volatility, is similar to the increase in the predicted cross-sectional mean of volatility observed in Figure II. While we estimate a positive and significant trend in the Long-run Component of volatility term, this increase is dwarfed by the positive trend in the transitory component term. This finding confirms our prior result despite the potential upward bias in the transitory component parameter in the rolling firm-level estimation due to the dynamics of firm characteristics over the estimation window.

While the coefficients on firm characteristics in this estimation are not directly comparable to those in the previous analysis, almost all of the firm characteristics are statistically significant (Age is the exception). We again observe the listing group effect of Brown and Kapadia (2007) from firms listing pre-1965 through those listing between 1985 and 1994. More recently listed firms, while still more risky than their pre-1965 counterparts, are slightly less risky than firms listing in the late 1980s and early 1990s.

6. Discussion and Conclusions

Using a variety of methods, the analysis in this paper shows that stock market volatility has increased significantly over the last few decades. The observed increase in firm volatility is largely attributable to increases in the transitory component of risk at the individual firm level with the cross-sectional average of the transitory component tripling over our sampling period. Moreover, the transitory component plays a more critical role in shaping the time-series variation of the mean of volatility in the later part of our sample. In fact, we find that after controlling for firm-specific characteristics, the long-run component of firm volatility has actually decreased through time. Panel regressions show that more illiquid firms, as well as firms with more volatile profits and high leverage, are especially susceptible to an amplification of innovations to volatility. These findings shed new light on the debate regarding trends in firm-level volatility while connecting this literature to more complex volatility models.[24]

These results have implications for a variety of issues in financial economics. For example, the dramatic swings in volatility over the last couple of decades may have been largely unexpected for many stock investors. This may have left some investors with more risk, and therefore more invested in stocks, than desired. Our results indicate that the increased importance of the transitory component must be accounted for in optimal portfolio decisions that rely on estimates of firm-level risk. In addition, casual observation suggests that other asset classes such as commodities and real estate may also be experiencing a trend toward higher transitory components. In contrast, the transitory component of volatility for U.S. government bonds appears to be declining. For baby-boomers in particular, the increase in risk coincides with prime saving years and an increased need for savings as overall household wealth has declined recently. In fact, current data from the Survey of Consumer Finance documents a slight decline in the percentage of households with stock investments. Future research might investigate if there exists a causal link between baby-boomers willingness to take more risk and the increase in the transitory component of volatility.

Recent research suggests that financial market development may play a role in allowing new, typically higher risk, firms to grow and eventually overtake in size established low risk firms (Comin and Mulani, 2009; Liang, McLean, and Zhao, 2010). In addition, theory suggests that as markets develop, competition increases in the financial sector and capital availability increases. This supply shock in turn drives down the cost of external capital which can result in the financing of firms with riskier fundamentals (see, for example, Baker, Stein, and Wurgler (2003), and cites therein). While this risk might manifest itself in the form of errors in allocation of capital, it also can drive

[24]See for example earlier work on single-factor models by Hull and White (1987); Melino and Turnbull (1990, 1991); Scott (1987); Wiggins (1987). See also work on multi-factor models by Engle and Lee (1999); Engle and Rangel (2008); Engle, Ghysels, and Sohn (2009) and cites within.

improvement in information (e.g., accounting) disclosure and legal standards which feeds back into further financial market development (Rajan and Zingales, 1998, 2003).

Figure V reinforces this link by plotting long-run market volatility against a measure of U.S. equity market development over the period 1926 to 2011.[25] Both series share a pronounced U-shaped pattern. Market risk and equity market development both decrease following the Great Depression. These measures stayed low as the demand for equity issues stagnated through the 1940s and 1950s and the value of publicly traded equity scaled by GDP remained depressed until the 1960s. Then with increased stock market participation by the baby-boomers and an increase in households' appetite for risk, both measures sharply increase through tech bubble in the 1990s and remain high following the financial crisis. Taken with our other results, these patterns suggest that previously documented relations between equity market development and firm risk are actually related to the transitory component of volatility.

Finally, other recent models have explored the role of time-varying risk in asset pricing (Drechsler and Yaron, 2011). The increasing level of the transitory component suggests that risk premiums in these models may be non-stationary if the effect of increasing the transitory component is more important than the effect of declining long-run volatility. Consequently, observed trends in firm risk may be associated with financial market development in ways that have broad implications for

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[25] We estimate our equity market development factor by adapting the dynamic factor model of Stock and Watson (1991) given below:

$$\begin{aligned}
\Delta y_{i,t} &= \gamma_i \Delta c_t + e_{i,t} \\
e_{i,t} &= \psi_{i1} e_{i,t-1} + \psi_{i2} e_{i,t-2} + \varepsilon_{i,t}, \quad \varepsilon_{i,t} \overset{iid}{\sim} N(0, \sigma_i^2) \\
\Delta c_t &= \phi_1 \Delta c_{t-1} + \phi_2 \Delta c_{t-2} + w_t, \quad w_t \overset{iid}{\sim} N(0,1)
\end{aligned} \tag{19}$$

In this model, we observe $\Delta y_{i,t} = \Delta Y_{i,t} - \overline{\Delta Y_i}$ where $\Delta Y_{i,t}$ is the change in the log of an economic indicator and $\overline{\Delta Y_i}$ is the time-series mean of $\Delta Y_{i,t}$. Similarly, $\Delta c_t = \Delta C_t - \delta$ is the deviation in the change in the log of the latent factor, ΔC_t from its mean, δ.

We utilize a set of equity market development indicators identified in previous research (see, for example, Rajan and Zingales (2003) and Bekaert, Harvey, Lundblad, and Siegel (2007)). For our observations, we use changes in logs of the following measures: the average market capitalization of common shares in CRSP; the total dollar volume of traded common shares scaled by total market capitalization from CRSP; the number of IPOs from Ibbotson, Ritter, and Sindelar (1994); and the sum of the squared market capitalizations scaled by total market capitalization of common shares in CRSP. Since the IPO data starts in 1960, we use the change in log number of distinct permnos from CRSP as an additional measure. Data are monthly and are collected from January 1926 to December 2011.

We estimate the factor model using the Kalman Filter and MLE. See Kim and Nelson (1999), Chapter 3 for a discussion of the estimation of this class of model using MLE and Section 3.5 for a discussion of this particular model.

the capital formation process, real economic growth, and regulatory policy.

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Figure I: Market Volatility

This graph depicts the trends in market volatility for the sample between 1964 and 2011. Market volatility is the monthly annualized standard deviation of daily returns of the CRSP Value Weighted Index. The series is overlaid with the predicted values from a linear trend estimation.

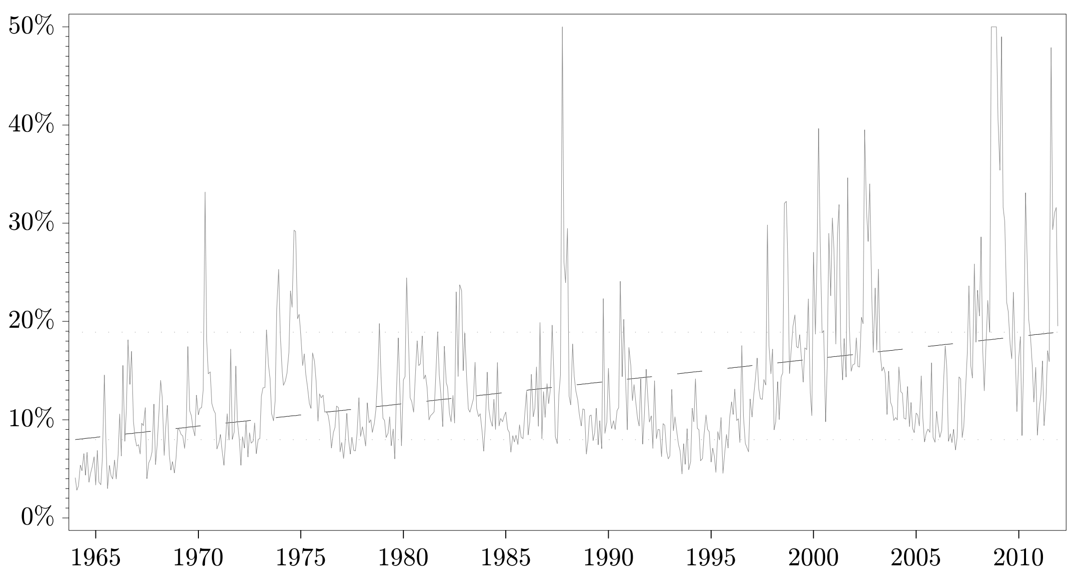
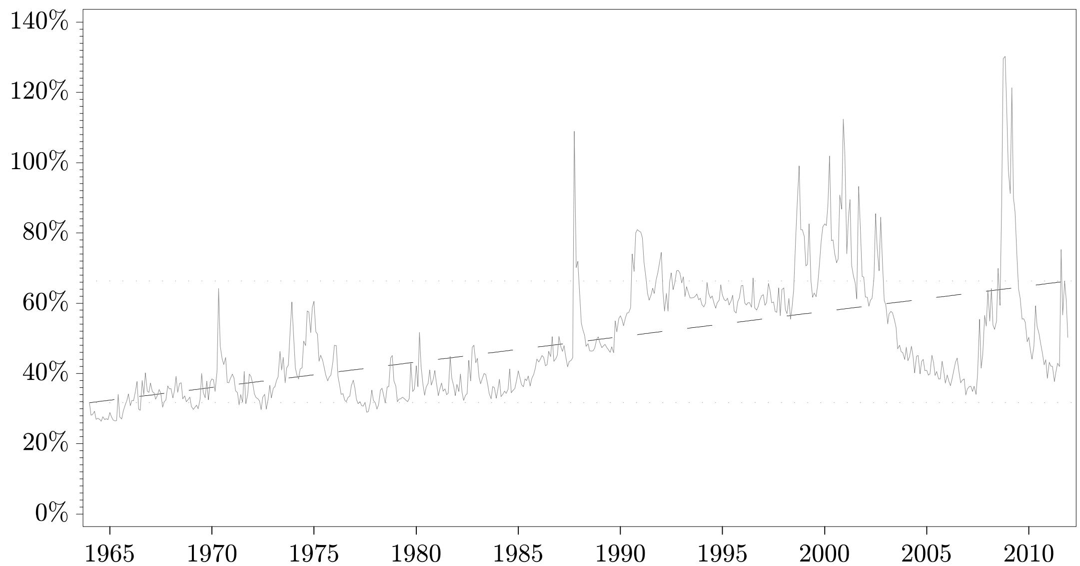


Figure II: Simple Volatility Estimates

This graph depicts the trends in the simple volatility estimates for the sample between 1964 and 2011. Equal-weighted Mean of Volatility is the cross-sectional average of monthly annualized standard deviations of daily stock returns from CRSP. Cross-sectional Standard Deviation of Volatility is the cross-sectional standard deviation of monthly annualized standard deviations of daily stock returns from CRSP. Each series is overlaid with the predicted values from a linear trend estimation.

Panel A: Equal-weighted Mean of Volatility



Panel B: Cross-sectional Standard Deviation of Volatility

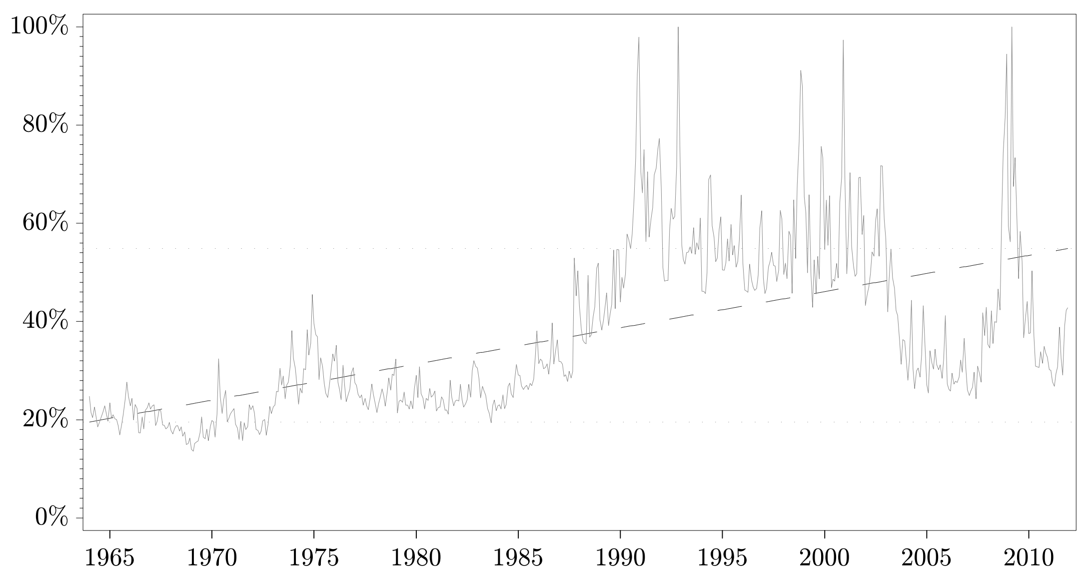
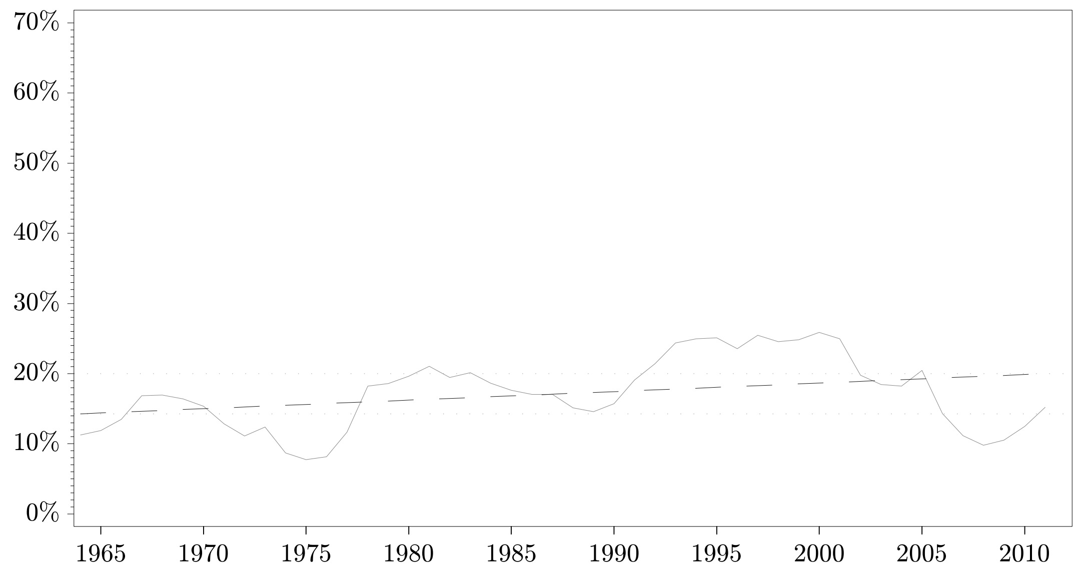


Figure III: Trends in the Components of Volatility

This graph depicts the trends in the cross-sectional average of the components of volatility for each year in the sample period of 1964 and 2011. The Long-run Component of Volatility and the Transitory Component are defined by equations (4)–(5). Each series is overlaid with the predicted values from a linear trend estimation.

Panel A: Long-run Component



Panel B: Transitory Component

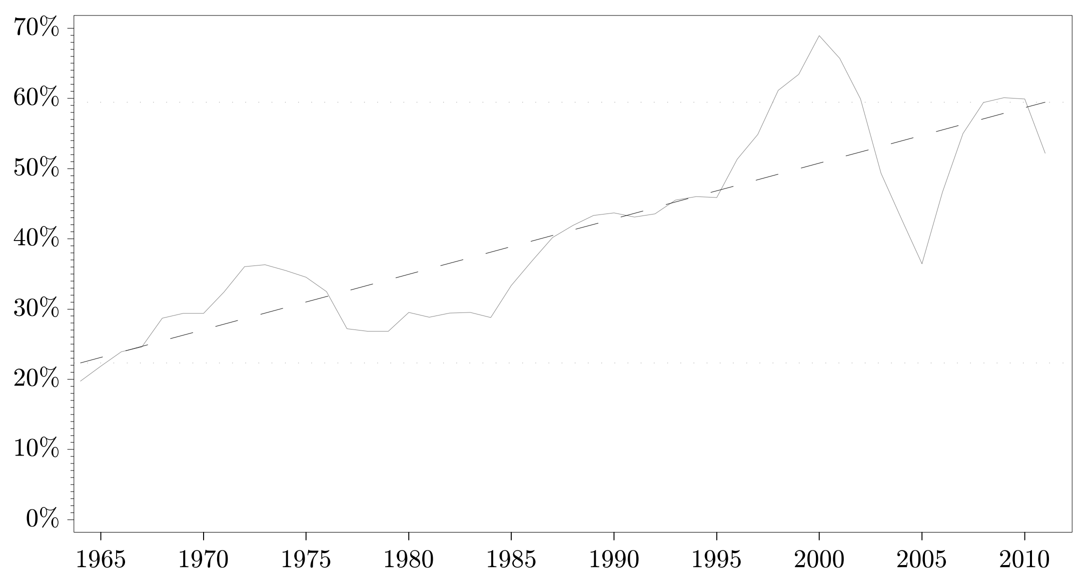


Figure IV: Attributes of the Trend in the Transitory Component

This graph depicts the results of the attribution analysis of the trend in the Transitory Component described in section 4.4. The dashed line presents the predicted cross-sectional means of the Transitory Component evaluated at the full sample sensitivities and full sample means with the predicted linear trend. The red line presents the predicted cross-sectional means of the Transitory Component evaluated at the full sample sensitivities and time-varying means. The black line presents the predicted cross-sectional means of the Transitory Component evaluated at both time-varying sensitivities and time-varying means.

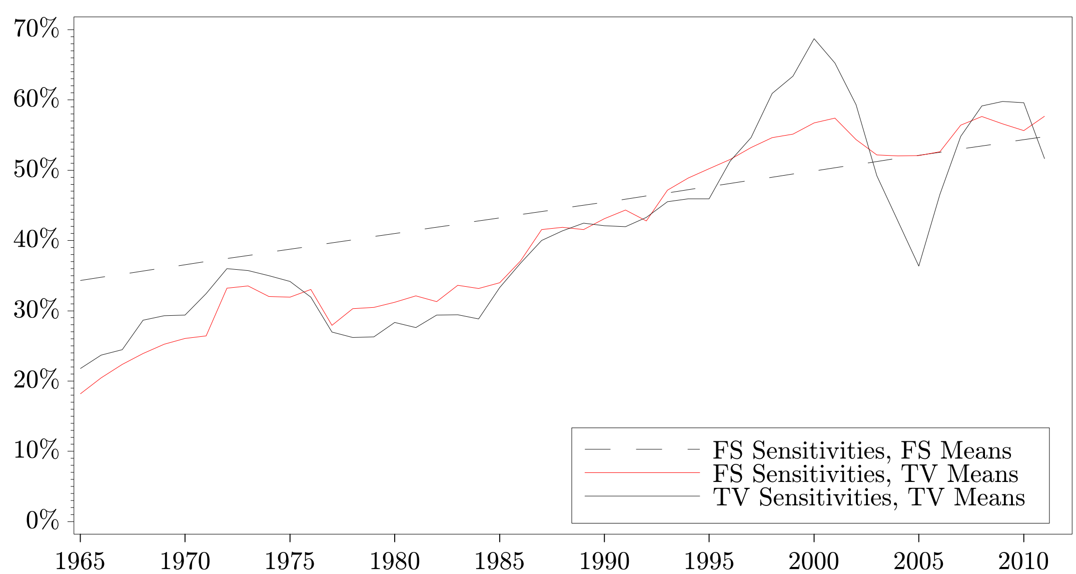


Figure V: Market Volatility and Equity Market Development

This graph plots the 10-yr Annualized Market Volatility against our Equity Market Development Factor. 10-yr Annualized Market Volatility is equal to the centered 10-yr rolling standard deviation of the daily return on the CRSP Value-weighted Index in excess of the return on the one-month U.S. Treasury bill. For details on the construction of the Equity Market Development Factor, see footnote 25. Since the starting index level is unidentified, we arbitrarily rescale our Equity Market Development Factor such that the minimum index value is equal to the minimum of the 10-yr Annualized Market Volatility. Monthly data points are plotted from the introduction of the CRSP Value-weighted Index in July 1926 to December 2011.

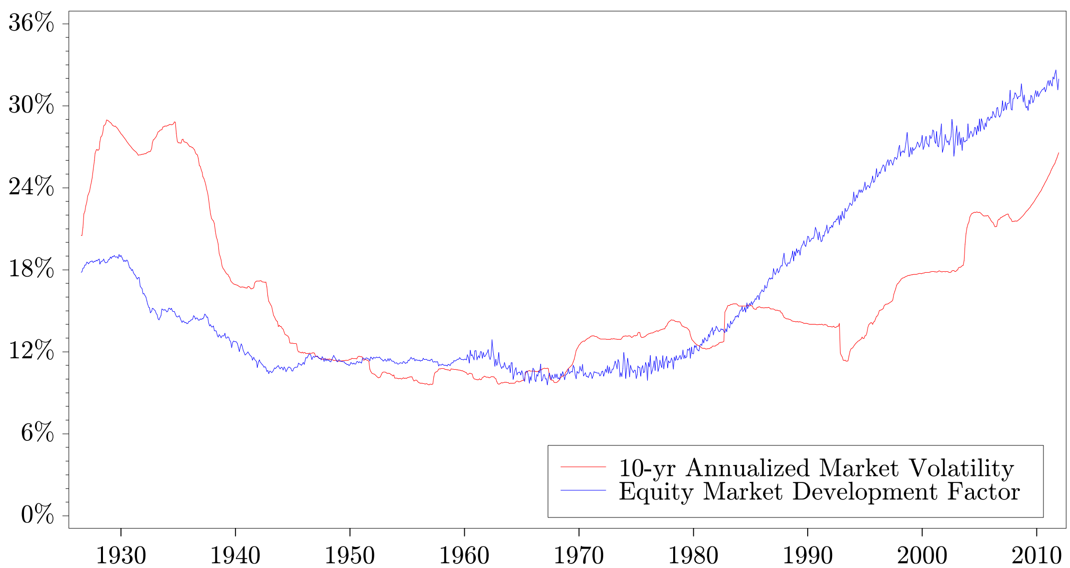


Table I: Market Volatility by Sub-period

This table reports summary statistics for market volatility for the period 1964 and 2011. Market volatility is the monthly annualized standard deviation of daily returns of the CRSP Value Weighted Index. Average Volatility is the mean of volatility within the sub-period. Number of Months is the number of monthly observations in the sub-period. Volatility > Sample Mean, Volatility > 20%, and Volatility > 30% are the number of months within the subperiod where market volatility exceeds the sample mean, 20%, and 30%, respectively. Std Dev of Volatility is the standard deviation of market volatility within the sub-period.

		Number of Months				
Period	Average Volatility	Total	Volatility > Sample Mean	Volatility > 20%	Volatility > 30%	Std Dev of Volatility
1964-1979	10.39	192	41	9	1	5.01
1980-1995	11.85	192	52	11	1	6.72
1996-2011	18.08	192	122	50	22	10.54
1996-2011 (ex. 2008-2009)	16.33	168	100	34	13	7.59

Table II: Linear Trends for Market Volatility

This table reports the coefficient on a linear trend and the corresponding p-Value for market volatility for the sample between 1964 and 2011. Market volatility is the monthly annualized standard deviation of daily returns of the CRSP Value Weighted Index. The model estimated is $y_t = \alpha + \beta\ t$ where $t = year - 1964$. The BHZ indicator takes the value 1 when the year is in a high variance regime as defined by Bekaert, Hodrick, and Zhang (2012) and 0 otherwise.

	Market Volatility
Panel A: Linear Trend	
Annual Trend	0.228%
p-Value	<.001
Panel B: Linear Trend with BHZ Indicator (1964-2009)	
Annual Trend	0.146%
p-Value	<.001
Panel C: Linear Trend (1964-2007)	
Annual Trend	0.146%
p-Value	<.001

Table III: Linear Trends for Naïve Volatility Estimates

This table reports the coefficient on a linear trend and the corresponding p-Value for naïve volatility estimates for the sample between 1964 and 2011. Naïve Mean of Volatility is the mean of five year rolling windows of monthly annualized standard deviations of daily stock returns from CRSP in percent. Naïve Transitory Component is the standard deviation of five year rolling windows of monthly annualized standard deviations of daily stock returns from CRSP in percent. For each model, $t = year - 1964$. The between estimation takes the form $\bar{y}_t = \alpha + \beta\ t$ where $\bar{y}_t$ is the mean across firms of Naïve Mean or Transitory Component in a given year. The fixed effects estimation takes the form $y_{i,t} = \alpha_i + \beta\ t$ where $y_{i,t}$ is the naïve estimate for firm i in year t. The BHZ indicator takes the value 1 when the year is in a high variance regime as defined by Bekaert, Hodrick, and Zhang (2012) and 0 otherwise.

	Naïve Mean of Volatility	Naïve Transitory Component
Panel A: Linear Trend		
Between Estimate		
Annual Trend	0.711%	0.501%
p-Value	<.001	<.001
Firm-level Fixed Effects		
Annual Trend	0.005%	0.233%
p-Value	0.293	<.001
Panel B: Linear Trend with BHZ Indicator (1964-2009)		
Between Estimate		
Annual Trend	0.648%	0.453%
p-Value	<.001	<.001
Firm-level Fixed Effects		
Annual Trend	−0.102%	0.177%
p-Value	<.001	<.001
Panel C: Linear Trend (1964-2007)		
Between Estimate		
Annual Trend	0.766%	0.488%
p-Value	<.001	<.001
Firm-level Fixed Effects		
Annual Trend	−0.073%	0.166%
p-Value	<.001	<.001

Table IV: Correlation Matrix of Volatility Esitmates

This table reports the Pearson correlation coefficients among the naïve volatility estimates, volatility measures from the Heston and Nandi (2000) GARCH estimation, and the components of the mean of volatility for the sample between 1964 and 2011. Naïve Mean of Volatility is the mean of five year rolling windows of monthly annualized standard deviations of daily stock returns from CRSP. Naïve Transitory Component is the standard deviation of five year rolling windows of monthly annualized standard deviations of daily stock returns from CRSP. Mean Squared Error is the mean squared error from the Heston and Nandi (2000) GARCH model presented in equation (1)–(2). Mean of Predicted Volatility is the sample mean of the annualized predicted volatilities from the Heston and Nandi (2000) GARCH model. Volatility of Predicted Volatility is the sample standard deviation of the annualized predicted volatilities from the Heston and Nandi (2000) GARCH model. Mean of Volatility is the long-run mean of volatility given in equation (3). The Long-run Component and the Transitory Component are the components of Mean of Volatility given in equations (4)–(5) respectively.

	Naïve Transitory Component	Mean Squared Error	Mean of Predicted Volatility	Volatility of Predicted Volatility	Mean of Volatility	Long-run Component	Transitory Component
Naïve Mean of Volatility	0.851	0.990	0.996	0.778	0.985	0.379	0.911
Naïve Transitory Component		0.913	0.865	0.912	0.887	0.190	0.882
Mean Squared Error			0.991	0.835	0.989	0.347	0.928
Mean of Predicted Volatility				0.809	0.994	0.397	0.914
Volatility of Predicted Volatility					0.850	0.230	0.849
Mean of Volatility						0.385	0.928
Long-run Component							0.038

Table V: Volatility Components by Sub-period

This table reports the mean and median values across firms within a given time period of the time-series medians of a firm's components of volatility. The Long-run Component and the Transitory Component are defined by equations (4)–(5) and are estimated for each firm-year using rolling five-year windows of daily returns.

		Long-run Component		Transitory Component	
Period	# of Firms	Mean	Median	Mean	Median
1964-1969	788	16.90%	13.20%	27.28%	23.91%
1970-1979	1,336	14.76%	6.67%	34.45%	31.28%
1980-1989	3,937	19.55%	16.87%	42.76%	37.18%
1990-1999	9,009	27.01%	21.01%	60.08%	49.81%
2000-2011	7,738	20.57%	7.31%	62.53%	53.60%
1964-2011	12,740	23.39%	16.11%	60.04%	50.59%

Table VI: Linear Trend Estimates for Components of Volatility

This table reports the coefficient on a linear trend and the corresponding p-Value for each of the components of volatility for the sample between 1964 and 2011. The Long-run Component and the Transitory Component are defined by equations (4)–(5) and are in percents. For each model, $t = year - 1964$ and the between estimation takes the form $\bar{y}_t = \alpha + \beta\ t$ where $\bar{y}_t$ is the mean across firms of the volatility component in a given year. The fixed effects estimation takes the form $y_{i,t} = \alpha_i + \beta\ t$ where $y_{i,t}$ is the volatility component for firm i in year t. The BHZ indicator takes the value 1 when the year is in a high variance regime as defined by Bekaert, Hodrick, and Zhang (2012).

	Long-run Component	Transitory Component
Panel A: Linear Trend		
Between Estimate		
Annual Trend	0.122%	0.791%
p-Value	0.028	<.001
Firm-level Fixed Effects		
Annual Trend	−0.249%	0.187%
p-Value	<.001	<.001
Panel B: Linear Trend with BHZ Indicator (1964-2009)		
Between Estimate		
Annual Trend	0.156%	0.696%
p-Value	0.013	<.001
Firm-level Fixed Effects		
Annual Trend	−0.225%	0.059%
p-Value	<.001	<.001
Panel C: Linear Trend (1964-2007)		
Between Estimate		
Annual Trend	0.226%	0.798%
p-Value	<.001	<.001
Firm-level Fixed Effects		
Annual Trend	−0.165%	0.071%
p-Value	<.001	<.001

Table VII: Variance Decomposition

This table reports the mean and median values of the variance decomposition given by equation (7) across firms within a given time period. The Long-run Component and the Transitory Component are defined by equations (4)–(5) and are estimated for each firm-year using daily returns between 1964 and 2011. A firm is required to have at least 6 observations in the stated period to be included in the analysis.

		Long-run Component		Transitory Component	
Period	# of Firms	Mean	Median	Mean	Median
1964-1969	419	0.475	0.490	0.525	0.510
1970-1979	900	0.320	0.314	0.680	0.686
1980-1989	1,555	0.299	0.290	0.701	0.710
1990-1999	3,610	0.345	0.335	0.655	0.665
2000-2011	3,900	0.243	0.180	0.757	0.820
1964-2011	7,230	0.279	0.251	0.721	0.749

Table VIII: Volatility Components and Firm Characteristics

This table reports the mean and median values across firms within a given characteristic group of the time-series median of a firm's components of volatility. The Long-run Component and the Transitory Component are defined by equations (4)–(5) and are estimated for each firm-year using rolling five-year windows of daily returns. Quintiles are assigned based on the time-series median of each firm's observations. Firm characteristics are defined in the text.

	# of Firms	Long-run Component	Transitory Component
Book-to-Market Quintiles			
1 (lowest)	2,464	29.88%	70.87%
2	2,465	23.89%	57.15%
3	2,465	20.21%	52.18%
4	2,465	18.88%	50.70%
5 (highest)	2,464	23.04%	68.42%
Size Quintile			
1 (smallest)	2,546	33.86%	97.77%
2	2,547	25.79%	64.26%
3	2,546	23.25%	53.71%
4	2,547	20.39%	47.35%
5 (largest)	2,546	13.54%	37.35%
Amihud Ratio Quintiles			
1 (lowest)	2,546	20.12%	54.67%
2	2,547	23.59%	50.81%
3	2,546	21.71%	53.68%
4	2,547	20.43%	51.55%
5 (highest)	2,546	30.98%	89.72%
Listing Group			
pre-1970	1,564	17.08%	36.02%
1970-1979	1,267	17.72%	41.83%
1980-1989	2,660	21.61%	58.68%
1990-1999	5,526	28.16%	68.83%
2000-2011	2,128	21.62%	63.10%

Table VIII: Volatility Components and Firm Characteristics (cont.)

	# of Firms	Long-run Component	Transitory Component
Profit Volatility Quintiles			
1 (lowest)	2,407	18.04%	42.43%
2	2,407	18.66%	45.87%
3	2,407	20.50%	52.54%
4	2,407	24.07%	66.32%
5 (highest)	2,407	34.33%	90.92%
R&D Share			
≤ 0	8,115	19.85%	55.28%
0 to 0.50	1,718	22.85%	55.29%
0.50 to 0.75	1,161	30.36%	62.69%
> 0.75	1,946	35.26%	78.28%
Leverage			
≤ 0	5,509	23.03%	55.97%
0 to 0.25	1,991	26.23%	61.97%
0.26 to 0.41	1,824	21.12%	56.01%
0.41 to 0.56	1,797	20.69%	53.47%
> 0.56	1,926	26.59%	75.08%
Age			
1-4	10,877	26.91%	61.78%
5-10	7,551	22.51%	56.85%
11-20	5,147	18.45%	49.89%
20+	2,425	13.32%	42.15%

Table IX: Determinants of Firm-level Volatility Characteristics

This table reports the model estimates for the Long-run Component and the Transitory Component in percents, as defined by equations (4)–(5). Estimates are obtained for each firm-year using rolling five-year windows of daily returns. To avoid modeling the unknown correlation structure in the components of volatility induced by these rolling windows, we take a single observation for each firm in each non-overlapping five-year window: 1967-1971, 1972-1976, ... , and 2007-2011. The components of volatility are set equal to the estimate for the center year of each window. Independent variables are equal to the mean value of the specific firm-characteristic over the five-year window. Marginal effects are calculated as the change in the dependent variable at a perturbation of one standard deviation for continuous variables and a discrete change from 0 to 1 for binary variables. Variable definitions are given in the text. Effects are fixed at the industry-level with industry definitions available from Kenneth French's website. Standard errors are clustered at the firm-level. *, **, and *** denote significance at the 5 percent, 1 percent and 0.1 percent levels respectively.

	Long-run Component			Transitory Component		
Parameter	Estimate	p-Value	MFX	Estimate	p-Value	MFX
Annual Trend (%)	−0.027	0.195		0.393***	<.001	
Amihud Ratio (log)	0.985**	0.003	0.87%	12.283***	<.001	10.80%
Size (log)	−2.198***	<.001	−4.09%	−0.650***	<.001	−1.21%
Book-to-Market Ratio	−2.451***	<.001	−1.22%	0.707	0.097	0.35%
Profit Volatility (log)	1.070***	<.001	1.75%	6.589***	<.001	10.75%
R&D Share	8.597***	<.001	2.65%	3.023***	<.001	0.93%
Leverage	0.407	0.549	0.13%	12.921***	<.001	4.11%
Age (log)	−4.382***	<.001	−4.25%	−2.435***	<.001	−2.36%
Listing Group (ref: pre-1965)						
1965-1974	−1.596***	<.001		−1.097*	0.049	
1975-1984	−2.266**	0.002		2.774***	<.001	
1985-1994	−2.831***	<.001		5.869***	<.001	
1995-2004	−5.188***	<.001		7.527***	<.001	
2005-2011	−11.300***	<.001		10.460***	<.001	
Fixed Effects	Industry			Industry		
Adjusted R-squared	0.161			0.512		
Number of Firm-Years	23,432			23,432		

Table X: Attributes of the Trend in the Transitory Component of Volatility

This table reports the results of the attribution analysis described in section 4.4. The Transitory Component are defined by equations (4)–(5) and is estimated for each firm-year using rolling five-year windows using daily return data. Change in Means is the change in the mean of the Transitory Component in percents attributable to changes in sample composition through time. Change in Sensitivities is the change in the mean of the Transitory Component in percents attributable to changes in sensitivities over the sample period. Total Change is the total change in the mean of the Transitory Component in percents attributable to a given independent variable.

	Change in Means	Change in Sensitivities	Total Change
Firm Characteristics			
Amihud Ratio (log)	2.93%	−0.84%	2.09%
Size (log)	0.56%	−8.30%	−7.73%
Book-to-Market Ratio	0.06%	4.45%	4.52%
Profit Volatility (log)	8.52%	−8.18%	0.34%
R&D Share	0.66%	−0.93%	−0.27%
Leverage	−2.05%	1.17%	−0.88%
Age (log)	−0.10%	7.47%	7.38%
Subtotal	10.58%	−5.14%	5.44%
Listing Group Effects			
1965-1974	−0.02%	0.65%	0.63%
1975-1984	0.22%	0.20%	0.42%
1985-1994	1.44%	0.07%	1.51%
1995-2004	3.00%	0.13%	3.13%
2005-2011	1.13%	0.82%	1.96%
Subtotal	5.78%	1.87%	7.66%
Industry Effects (Subtotal)	0.42%	4.40%	4.82%
Total Explained Change	16.78%	1.13%	17.92%
Unexplained Time Trend			12.35%

Table XI: Linear Trend Estimates for Alternative GARCH Models

This table reports the coefficient on a linear trend and the corresponding p-Value for each of the alternative GARCH models for the sample between 1964 and 2011. Std Dev of s, Persistence of s and s Share are measures based on the component GARCH model and are defined in the text. Mean of h_t, Vol of h_t, α and d are measures based on the FIEGARCH model and are defined in the text. For each model, $t = year - 1964$ and the between estimation takes the form $\bar{y}_t = \alpha + \beta\, t$ where $\bar{y}_t$ is the mean across firms of the volatility component in a given year. The fixed effects estimation takes the form $y_{i,t} = \alpha_i + \beta\, t$ where $y_{i,t}$ is the volatility component for firm i in year t. The BHZ indicator takes the value 1 when the year is in a high variance regime as defined by Bekaert, Hodrick, and Zhang (2012).

	Component GARCH Measures			FIEGARCH Measures		
	Std Dev of s	Persistence of s	s Share	Mean of h_t	Vol of h_t	d
Panel A: Linear Trend						
Between Estimate						
Annual Trend	0.010	0.003	0.177%	0.452%	0.444%	0.002
p-Value	<.001	<.001	<.001	<.001	<.001	<.001
Firm-level Fixed Effects						
Annual Trend	0.007	0.004	0.199%	−0.218%	0.041%	0.003
p-Value	<.001	<.001	<.001	<.001	<.001	<.001
Panel B: Linear Trend with BHZ Indicator (1964-2009)						
Between Estimate						
Annual Trend	0.007	0.002	0.123%	0.429%	0.418%	0.001
p-Value	<.001	0.017	0.022	<.001	<.001	0.019
Firm-level Fixed Effects						
Annual Trend	0.004	0.003	0.147%	−0.331%	−0.008%	0.003
p-Value	<.001	<.001	<.001	<.001	0.454	<.001
Panel C: Linear Trend (1964-2007)						
Between Estimate						
Annual Trend	0.009	0.002	0.104%	0.576%	0.477%	0.001
p-Value	<.001	0.013	0.002	<.001	<.001	0.049
Firm-level Fixed Effects						
Annual Trend	0.004	0.002	0.053%	−0.326%	−0.009%	0.002
p-Value	<.001	<.001	<.001	<.001	0.397	<.001

Table XII: Determinants of Firm-level Volatility Characteristics: Pooled Estimation

This table reports the model estimates for pooled estimation described in the text. Marginal effects are calculated as the change in the Mean of Volatility, defined in equation (3), given a perturbation of one standard deviation from the mean for continuous variables, a perturbation of one year from the mean for the quarterly trend and a discrete change from 0 to 1 for all observations for binary variables. Variable definitions are given in the text. Effects are fixed at the industry-level with industry definitions available from Kenneth French's website. *, **, and *** denote significance at the 5 percent, 1 percent and 0.1 percent levels respectively.

	Estimate	p-Value	MFX
Omega (Long-run Component)			
Quarterly Trend	0.014***	<.001	0.04%
Amihud Ratio (log)	−0.078***	<.001	−0.04%
Size (log)	−0.249***	<.001	−0.22%
Book-to-Market Ratio	−0.082**	0.009	−0.02%
Profit Volatility (log)	0.462***	<.001	0.64%
R&D Share	0.438***	<.001	0.10%
Leverage	0.887***	<.001	0.22%
Age (log)	−0.031	0.245	−0.01%
Listing Group (ref: pre-1965)			
1965-1974	0.237***	<.001	−0.25%
1975-1984	0.662***	<.001	0.02%
1985-1994	0.840***	<.001	0.20%
1995-2004	0.748***	<.001	0.10%
2005-2011	0.640***	<.001	0.00%
Alpha (Transitory Component)			
Quarterly Trend	0.018***	<.001	1.94%
Beta (Persistence of Volatility)			
Quarterly Trend	−0.015***	<.001	−1.37%
Fixed Effects	Industry		
Number of Firms	9,402		
Number of Firm-Quarters	519,236		