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Total Factor Productivity and Idiosyncratic Volatility Trends

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Abstract

Firms' idiosyncratic stock return volatility has become more volatile in the US since the 1960s. This paper investigates why individual stocks became more volatile over the 1964–2013 period using firm-level total factor productivity (TFP). On average, the volatility of idiosyncratic TFP growth rate has increased, being associated with higher idiosyncratic return volatility. The connection between TFP growth and economic profits provides an explanation for the increase in the idiosyncratic volatility of fundamental cash flows. The results are robust when using time-series and panel regressions and controlling for cash flow and earnings variability, size, book-to-market, leverage, profitability, age, dividend yield, and stock illiquidity.

JEL Classification: G 12 Asset Pricing, D 24 Production

Key words: Total Factor Productivity, Idiosyncratic Volatility

1. Introduction

Campbell et al. (2001) argue forcefully that the idiosyncratic volatility of individual firms in the US stock market follows an upward trend, although market and industry volatilities remain roughly stable. The increasing idiosyncratic volatility at the firm level has stimulated widespread interest in the recent literature as various factors are proposed to explain the trend. The major explanatory factors of the idiosyncratic volatility trend include return-on-equity and its volatility (Wei and Zhang, 2006), cash flow volatility (Irvine and Pontiff, 2009; Pae et al., 2018), growth options (Cao et al., 2008), firm age (Pastor and Veronesi, 2003; Fink et al. 2010), firm life cycle (Hasan and Habib, 2017), CEO's managerial power (Tan and Liu, 2016), product market competition (Philippon, 2003; Irvine and Pontiff, 2009; Abdoh and Varela, 2017) and retail trading (Brandt et al., 2010).

This study further investigates the fundamental mechanism behind the increase of idiosyncratic volatility during 1964–2013 as it is unclear what fundamental factors drive idiosyncratic volatility over time. Although the literature provides evidence that earnings and cash flow volatility increase with idiosyncratic return volatility, little is known about what drives earnings and cash flow volatility in the first place. This article argues that the volatility of the growth rate of total factor productivity (GTFP) has a significant impact on this puzzling upward trend in idiosyncratic return (as well as earnings and cash flow) volatility over time. Firm-level GTFP has a direct connection with production cost and profitability. Hence, its volatility should affect the volatility of cash flow and earnings. Consistent with an efficient market, this result is mirrored by an increase in idiosyncratic return volatility. Greater variability in productivity growth can be attributed to high research and development (R&D) activity and to the increase in the number of high-tech firms in the market. The observed increase in R&D-driven innovations documented in previous studies (i.e., Comin and Philippon, 2005) may be responsible for the increase in the uncertainty of TFP changes (positive or negative) and, hence, volatility.

This study is motivated because the upward trend in idiosyncratic volatility has important implications for portfolio diversification, event studies, option pricing, and macroeconomics. Many investors may fail to diversify in the manner recommended by financial theory, and, as a result, they are affected by shifts in idiosyncratic volatility. The price of an option (i.e., employee stock options) on an individual stock depends on the total volatility of the stock return, including idiosyncratic volatility. The statistical significance of abnormal event-related returns is determined by the volatility of individual stock returns relative to the market or industry (Campbell et al., 1997, Chapter 4). Finally, by focusing on idiosyncratic productivity shocks as a determinant of the observed return and cash flow volatilities, results based on real data (i.e., TFP) are probably more directly relevant for macroeconomics than those using financial data (i.e., earnings). Hence, the results of this study shed light on real economic risks, such as the idiosyncratic volatility of employment and wages.

Using data from 1964 to 2013, we document a noticeable increase in GTFP volatility over time. To determine whether this volatility is related to idiosyncratic return volatility, we conduct two sets of analyses. First, we show the time-series trend in return volatility is associated with time trends in GTFP volatility. Second, we verify that, in the panel-section, GTFP volatility explains the differences in idiosyncratic volatility. Consistent with the prediction of a positive relationship between productivity, profitability, and returns (e.g., Balvers and Huang, 2007; Stierwald, 2009), the results from the regressions indicate a strong association between increasing idiosyncratic return volatility and GTFP volatility. We control for several potential confounds such as book-to-market ratio, leverage, size, age, the level of profitability, dividend yield, and trading illiquidity measure. More importantly, the association remains economically and statistically significant after adding earnings and cash flow volatility variables, indicating that GTFP volatility can provide a deeper fundamental explanation of the increased idiosyncratic return volatility.

The findings in paper is related to the work of Comin and Mulani (2009), which argues that an industry level R&D increase is associated with a firm-level volatility increase and a market-level volatility decrease. We bring two new pieces to their findings. First, we directly test whether firm-level (rather than industry- or sector-level) TFP growth rate (GTFP) volatility has been increasing over time. Second, we document an association between GTFP and return volatilities.

The rest of the study is constructed as follows. Section 2 reviews the relevant literature. Section 3 explains the dataset and the research design. Sections 4 and 5 discuss main results and robustness results. Section 6 concludes.

2. Literature Review

2.1. Idiosyncratic Volatility of Stock Return

Idiosyncratic volatility (IV) of stock return has increased over time, while the volatility of stock market returns remained unchanged (Campbell et al., 2001). Some researchers attribute the increasing IV of stock return to the volatility of firm fundamentals. To name a few, Wei and Zhang (2006) present that return-on-equity (ROE) is negatively related with IV of stock return, while ROE volatility is positively related with IV of stock return. Cao et al. (2008) establish a strong link between firm growth options and the trend in stock return IV. Irvine and Pontiff (2009) argue that the increasing IV of cash flow is the main driving force of the increasing IV of stock return. Pae et al. (2018) further document that the volatility of three DuPont ROE components, which are asset turnover, profit margin and equity multiplier, explain major portions of the IV of stock return.

Some other researchers argue that a variety of firm characteristics determines the IV of stock return. For example, young or no-dividend stocks have more volatile stock returns (Pastor and Veronesi, 2003). Firm maturity changes explain most of the increase in IV of stock return (Brown and Kapadia, 2007; Fink et al., 2010). Firm life cycles and the IV of stock return demonstrate a U-shape relationship (Hasan and Habib, 2017). CEO's managerial power is also associated with a lower IV of stock return (Tan and Liu, 2016). Moreover, Philippon (2003), Gaspar and Massa (2006), Irvine and Pontiff (2009), Abdoh and Varela (2017), provide evidence from different countries/perspectives to establish the causal relationship between product market competition and IV stock return.

2.2. Total Factor Productivity

Total Factor Productivity (TFP) is defined as the output residual not explained by either labor or capital, and used as a measure of production efficiency. Solow (1956) establishes that the growth of TFP is the major determinant of the long term economic growth in each country. Many researchers follow this line of literature and demonstrate that TFP is an important determinant of various macro-economic factors, using country or industry level data.

Recently, researchers begin to investigate the effects of TFP from micro-economic perspective and examine how firm level TFP affect firm excess returns. Vassalou and Apedjinou (2004) show that TFP provides important information about expected equity returns. Lieberman and Kang (2008) show that firm level TFP can be a better performance measure than profit rates. Chun et al. (2008, 2011) find that information technology systematically affects firm-specific volatility. Comin and Mulani (2009) find that an increase in firm-level volatility is driven by an increase in R&D, which is a key determinant of TFP growth.

Imrohoroglu and Tuzel's (2014) further document a positive relationship between TFP and stock returns using firm level data. Chun et al. (2016) find that the stock return of a firm is affected not only by its own TFP, but also by the aggregate TFP. Ball et al. (2017) show that portfolio and firm-level earnings are significantly affected by TFP changes. Abdoh (2019) finds that productivity shocks have positive and significant impacts on profitability. Given the ample evidence that TFP affects firm profitability and stock returns, we should expect a positive association between TFP volatility and profitability and return volatilities.

3. Methodology

3.1 Sample

The sample employs stock return data from CRSP files, accounting data from Compustat quarterly files, and TFP data from Tuzel's website (see Imrohoroglu and Tuzel, 2014).[1] Stock return data are available daily and monthly. Accounting data are available quarterly while TFP data are only available annually. The TFP data from Tuzel's website is only available from 1964 to 2013, which limit the usage of other data.

We exclude financial firms (SIC classification 6000–6999), regulated firms (SIC classification 4900–4999), and observations with non-positive data on sales, total assets, number of employees, gross property, plant, and equipment, depreciation, accumulated depreciation, and capital expenditures. Additionally, each stock should have complete trading data in the analyzed year.

[1] Retrieved from: https://sites.google.com/usc.edu/selale-tuzel/home?authuser=2.

This requirement reduces the effects of infrequent trading and the CRSP delisting return bias. As Gaunt (2004) argues, the larger the number of thinly traded stocks become, the less reliable the calculated returns are[2].

3.2 Constructing Volatility Measures

The empirical analysis focuses on the impact of IV of GTFP (IV_GTFP) on IV of stock return (IV_RET), IV of earnings (IV_EARN) and IV of cashflow (IV_CF).

IV_RET

Following Campbell et al. (2001), and Irvine and Pontiff (2009), we estimate IV of stock return using the beta-free method of the unconditional single factor capital asset pricing model (CAPM). The estimation is shown below:

$$\text{IV\_RET}_t = \frac{1}{j} \sum_{s=1}^{t} (\text{R}_{is} - \text{R}_{ms})^2 \qquad (1)$$

where IV_RET is the yearly (t) cross sectional average idiosyncratic return volatility, j is the total number of firms, R_{is} is the daily return for firm i, and R_{ms} is the market return obtained from equally weighted index of all stocks.

Consistent with Schwert (1989), the above equation computes annual variances based on non-overlapping samples of monthly or daily data. Using non-overlapping samples to estimate the variance makes estimation error uncorrelated over time. To construct yearly volatility series based on monthly returns we change the return in Equation (1) from daily to monthly, while keeping time interval t as one year. Using monthly data ensures additional robustness because autocorrelation of monthly stock returns is weaker than that of daily returns. Firms also have fewer missing observations when returns are measured on a monthly basis.

IV_CF and IV_EARN

Following Irvin and Pontiff (2009), we use earnings and cash flow as fundamental variables. We construct IV_EARN and IV_CF using the equation below:

$$E_{iq} - E_{iq\text{-}4} = \alpha + B_1 (E_{iq\text{-}1} - E_{iq\text{-}5}) + B_2 (E_{iq\text{-}2} - E_{iq\text{-}6}) + B_3 (E_{iq\text{-}3} - E_{iq\text{-}7}) + \varepsilon_{iq} \qquad (2)$$

Where E_{iq} are vectors of earnings per share (Compustat data item 19), or cash flow per share[3] (Compustat data item 19 plus item 5), for firm i in quarter q. This model is estimated at the industry level for each of the 49 industry groups defined by Fama and French (1997). The intercepts and slopes hence vary at the industry level.

Since idiosyncratic volatility (IV) is by definition unpredictable, the idiosyncratic earnings are measured by the error term of the model (ε_{iq}), which accounts for serial correlation, reflecting

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[2] This trading data restriction indicates many firms are removed from the sample year when daily stock return data is required, yet much less firms are removed when monthly stock return is required.
[3] Cash flow per share is calculated as earnings per share plus depreciation.

idiosyncratic profitability. The idiosyncratic cash flow is measured similarly using Equation (1), by replacing earning per share with cash flow per share.

To derive aggregate statistics, we use the residuals from Equation (2) to calculate the annual volatility of idiosyncratic earnings and cash flow for year t as:

$$\text{IV\_}\varepsilon_t = \sum_{q=1}^{4} \frac{1}{j} \sum_{i=1}^{j} \left(\varepsilon_{iq} - \varepsilon_{mq}\right)^2 \qquad (3)$$

Where IV_ε_t is the estimate of the idiosyncratic volatility in earnings (IV_EARN) or cash flow (IV_CF) for year t, q corresponds to a quarter, j is the total number of firms in a given quarter, and ε_{mq} is the mean of innovation in earnings or cash flow across firms in the quarter.

IV_GTFP

Given that the measure of TFP from Imrohoroglu and Tuzel (2014) is idiosyncratic, we take the annual difference in the logarithm of TFP for each firm as follows：

$$\text{GTFP}_{it} = \text{Log}\,[\text{TFP}_{it}] - \text{Log}\,[\text{TFP}_{it-1}] \qquad (4)$$

where GTFP is the growth rate of the idiosyncratic TFP. The idiosyncratic feature of the TFP data is the result of Imrohoroglu and Tuzel's (2014)'s estimation method. Particularly, firm-level TFP is free of the effect of industry or the aggregate TFP in any given year and deals with within firm serial correlation in productivity.[4]

TFP data is only available annually.[5] We do not estimate profit innovation using yearly data because it requires a longer time series interval in Equation (1), that is, eight instead of two years when using quarterly frequency.

Similarly, we construct an aggregate measure of GTFP volatility by determining the cross-sectional variance of GTFP in a year t as follows:

$$\text{IV\_GTFP}_t = \frac{1}{j} \sum_{i=1}^{j} (\text{GTFP}_{it} - \text{GTFP}_{mt})^2 \qquad (5)$$

Where j is the total number of firms in a given year and GTFP is the growth rate of annual TFP.

Overall, these estimations yield 50 years of IV_RET, IV_EARN, IV_CF and IV_GTFP data. In the calculation process of IV_RET, IV_EARN, IV_CF and IV_GTFP, we use equal-weighted portfolios, instead of value weighted portfolios, because we are interested in determining a volatility pattern representative of all firm size. To reduce the potential impacts of outliers, we use the natural logarithm of volatility in the following regressions.

[4] The TFP estimation from Imrohoroglu and Tuzel's (2014) has taken care of selection and simultaneity biases.

[5] Note that Imrohoroglu and Tuzel (2014) estimate TFP using firm-level data on sales, operating income and number of employees from Compustat, output and investment deflators from the Bureau of Economic Analysis, and wage data from the Social Security Administration. The choice to estimate annual, and not quarterly, TFP is due to data limitations at higher frequencies. For example, Compustat does not provide quarterly information on the number of employees.

4. Results

4.1. Graphical Analysis

In this section, we graphically present the time series of the idiosyncratic volatility of stocks return, earnings, cash flow and TFP growth from 1964 to 2013.

Figures 1 and 2 display the time series pattern of IV_RET. Figure 1 computes annual volatility based on daily data, while Figure 2 computes annual volatility based on monthly data. Consistent with Campbell et al. (2001), there appears to be a positive trend in the idiosyncratic volatility over the sample period. Both Figures 1 and 2 show spikes in volatility during the oil crisis of the 1970s and the stock market crash of 1987. Furthermore, a remarkable up and down in idiosyncratic return volatility coincides with the internet boom and bust of the late 1990s. Another significant increase in volatility happens around the 2008–2009 financial crisis. The fluctuations of idiosyncratic return volatility support the argument made by Schwert (1989), that stock volatility varies with economic activity and macroeconomic volatility.

<Insert Figures 1 and 2>

Figures 3 and 4 plot the time-series pattern of IV_EARN and IV_CF. As described earlier, IV_EARN and IV_CF reflect the unexpected shock to earnings and cash flow. Consistent with Irvine and Pontiff (2009), earnings and cash flow idiosyncratic volatility are, on average, increasing over time. The trend in idiosyncratic cash flow and earnings volatility mirrors the trend in idiosyncratic stock return volatility. For example, the high spike in IV_RET during 2008-2009 crises coincides with the spike in IV_EARN and IV_CF. Looking at all volatility plots, the different volatility measures tend to show the same positive time trend.

Figure 5 displays an upward trend in IV_GTFP, with spikes during the internet boom era and the 2008-2009 financial crisis. In sum, Figures 1 to 5 demonstrate that IV_RET (daily or monthly), IV_EARN, IV_CF and IV_GTFP all tend to have an upward trend over time.

<Insert Figures 3–5>

Figures 1 to 5 indicate that several stock market events had significant effects on all five-volatility series. These events might overshadow the rest of the sample and distort the results. To reduce the potential impacts of outliers, we use the natural logarithm of volatility. Taking the natural logarithm of volatility series can also reduce the impact of heteroskedasticity (Xu and Malkiel, 2003).

4.2. Descriptive Statistics

Panel A of Table 1 presents summary statistics for the time series of annual idiosyncratic volatility. All five volatility series exhibit substantial variation over time. The mean of LOG(IV_RET) from daily (monthly) data is -1.403 (-2.618) with a time-series standard deviation of .606 (0.638). Hence, estimating return volatility using daily data yields a higher mean than estimating return volatility using monthly data. The mean of LOG(IV_EARN), LOG(IV_CF) and LOG(IV_GTFP) are 0.897, 1.165 and 0.077, respectively. The standard deviation of these three series are 0.723, 0.491, 0.041, respectively. Comparing with the other four series, LOG(IV_GTFP) has a relatively lower mean and variation.

Panel B represents the correlation matrix among the idiosyncratic variances of returns, earnings, cash flow, and productivity, using Pearson's test. The highest correlation is found between monthly and daily estimated annual idiosyncratic volatilities (90%). The correlations between the LOG(IV_GTFP) and the four other variables all exceed 50%. Specifically, LOG(IV_GTFP) is more correlated with LOG(IV_EARN) (.73) than with LOG(IV_CF) (.55). All correlation measures are significant at about the 5% significance level, suggesting that fundamental volatilities and return volatilities are closely interrelated.

<Insert Table 1>

4.3. Aggregate Idiosyncratic Volatility Trend Estimates

To directly test for the presence of a time trend in the aggregate idiosyncratic volatility time series, we employ the following estimation method:

$$\text{Log (IV)}_t = \alpha + \text{TIME}_t + \varepsilon_t \qquad (6)$$

where IV is the idiosyncratic volatility, which is constructed from return, earnings, cash flow, or GTFP. Table 2 reports the results on these various time series. Panel A runs an ordinary least squares (OLS) regression that reports a generalized method of moments (GMM)-based t-ratio using the Newey–West type of adjustment for autocorrelation and conditional heteroscedasticity. Panel B applies the generalized least squares (Yule–Walker) method regression, which also accounts for autocorrelation. This method is advantageous in my setting, since we have a short time series. In both tests, the number of lags is determined by the "general to specific" method recommended by Campbell and Perron (1991) and Ng and Perron (1995). Specifically, we choose the optimal number of lags to be 12 and test whether the lag is statistically significant. If it is, we set the optimal number of lags to be 12; otherwise, we repeat the test while reducing the optimal number of lags by one, and so on.[6]

The results are consistent with the observations from the graphs. The trend coefficient confirms the presence of a positive time trend in the idiosyncratic volatility of returns, earnings, cash flow, and GTFP. The time trend of idiosyncratic volatility from using higher frequency data (daily returns of .0226 and .0241 in panels A and B, respectively) is lower than from the volatility using lower frequency data (monthly returns of .027 and .028 in panels A and B, respectively).

Using the OLS method, the trend coefficients are .0404 (4.8), and .022 (4.48) for earnings and cash flow volatilities, respectively, along with their t-statistics in parentheses. The trend

[6] The optimal number of lags is 9, 8, 12, 8, and 12 for the volatility from monthly data, volatility from daily data, earnings volatility, cash flow volatility, and GTFP volatility, respectively.

coefficients for each time series in panel A is close to its counterpart in panel B. The results are generally robust to the choice of estimation method in that, in general, the two approaches lead to consistent results (i.e., significant and positive coefficient estimates for the time trends of all volatility series). The focus of this study is GTFP volatility, which shares the same time trend as idiosyncratic fundamental and return volatility. The coefficient of its linear trend in panel A (B) is positive and significantly different from zero, .0024 with t-value = 7.46 (.0024 with t-value = 8.27). Overall, the results are consistent with past studies, showing evidence of a positive trend in firm idiosyncratic risk over time.

<Insert Table 2>

We provide evidence that GTFP volatility plays a significant role in driving the trend of idiosyncratic variance using the following a procedure similar to that of Cao et al. (2008). In step 1, we regress the idiosyncratic return volatility on a constant and earnings or cash flow volatility to remove any variation in the idiosyncratic volatility explained by the profit volatility. In step 2, we take the residuals from the first step and run two regressions: (a) first, we regress the residuals on an intercept and time trend, and test if the trend remains significant; (b) second, we add GTFP volatility to the regression in step (a) and test if it significantly affects the residuals. we repeat these two steps while switching profit volatility with GTFP volatility. If the time trend is insignificant in part (a) of step (2), the volatilities of profit or GTFP capture the trend. If the trend is significant in part (b), we can conclude that GTFP (profitability) volatility explains a trend in idiosyncratic variance that cannot be explained by the volatility of profitability (GTFP).

Table 3 shows the results of this test. Panel A displays the results when using annual idiosyncratic volatility estimated from daily returns, while Panel B displays the idiosyncratic volatility using monthly returns. In the column labeled “Step 2: a,” we first report the regression of the orthogonalized errors on the time trend. As shown in both panels, removing the idiosyncratic variance of profitability or GTFP does not yield a trend indicating the important role of fundamentals in explaining the positive trend of idiosyncratic return volatility. Given that TFP can drive firm profitability, its volatility may exert a greater impact on idiosyncratic return volatility. This point is investigated further in step 2: b, where we regress the orthogonalized errors on the variables not used in step 1. For example, if we remove the effect of earnings volatility from the trend in the first step, in the second step, we add the cash flow and GTFP volatility to examine if they can explain the residuals. After removing any variation in the return volatility explained by earnings (cash flow) volatility, GTFP volatility significantly and economically influences the residuals with a coefficient equal to 11.77, with t-value = 3.11 (13.27 and t-value = 3.34). Similarly, the residuals of annual volatility estimated from monthly returns are significantly explained by the GTFP volatility, as the coefficients are statistically significant at the 1% level after removing earnings (cash flow) volatility from idiosyncratic volatility: 12.23 with t-value = 3.26 (13.97, t-value = 3.4). The coefficient of earnings volatility remains a significant and positive explanatory variable of idiosyncratic variance after controlling for GTFP volatility. Nevertheless, the economic significance of the GTFP volatility is much higher than of earnings volatility in explaining the movement in residuals of idiosyncratic return variance (i.e., 13.27 versus .81). Moreover, if we remove the effect of cash flow volatility from the idiosyncratic variance, the residuals are positively and significantly explained by the GTFP volatility and not the earnings volatility.

These results indicate that the time-trend in volatility exhibited by the aggregate idiosyncratic return variance measure is more reflective of the trend in the underlying aggregate firm's GTFP volatility than that of the profit (earnings and cash flow) volatility. The findings are also consistent with the hypothesis that TFP growth volatility and profit volatility share a common trend, as TFP (i.e., efficacy) can determine profitability.

<Insert Table 3>

A limitation of the time-series test above is the potential small sample size (n = 50 years) and the consequent low statistical power. Additionally, there could be a spurious causality problem related to persistent time series such as return volatility.[7] To overcome these shortcomings, we conduct statistical analysis of panel, time series, and cross-sectional regressions. Although the primary focus of this paper is the time-series association between idiosyncratic return and GTFP volatilities, it is important to demonstrate the existence of such an association at the firm level.

4.4. Firm-Level Analyses

This section evaluates the impact of TFP growth volatility on the idiosyncratic variance of returns at the firm level after controlling for profit volatility and other determinants of idiosyncratic return volatility.

$$\text{Log (IV-RET)}_{it} = \alpha_o + \alpha_1 \text{ TIME}_t + \alpha_2 \text{ Log (IV- GTFP}_{it}) + \alpha_3 \text{ AGE}_{it} + \alpha_4 \text{ LEV}_{it} + \alpha_5 \text{ BM}_{it} + \alpha_6 \text{ SIZE}_{it} + \alpha_7 \text{ ROE}_{it} + \alpha_8 \text{ DY}_{it} + \alpha_9 \text{ ILLIQ}_{it} + \alpha_{10} \text{ Log (IV-EARN)}_{it} + \alpha_{11} \text{ Log (IV-CF)}_{it} + \varepsilon_{it} \quad (7)$$

where IV-RET is the stock return idiosyncratic volatility measured as annual variance of market-adjusted return (i.e., return minus market return). As above, we construct volatility from monthly or daily returns during the calendar year. we exclude firms that do not have a full year of uninterrupted returns data because disruptions in trading can lead to unusual information events, and we wish to explore the volatility of returns under normal operating circumstances.

TIME is a time trend variable that takes values from 1 to 50 for each of the years from 1964 to 2013. In this section, we construct the volatility measures by finding the time-series variance of fundamentals (earnings, cash flow and GTFP) at the firm level. For example, the idiosyncratic volatility measure for GTFP (IV-GTFP) is calculated from the annual GTFP using three observations from year t to year t - 2, IV-GTFP-3. As a robustness, we consider longer time intervals of four years (from year t to year t - 3, IV-GTFP-4) and five years (from year t to year t -

[7] Granger and Newbold (1974) caution that spurious relations could be inherent between two independent time series with time trends.

4, IV-GTFP-5). This procedure differs from the aggregate statistics for which the cross-sectional variance had to be estimated in order to obtain the measure of volatility in each year. In this section, we do not find the cross-sectional variance as we are focusing on firm-level volatility. The firm-level earnings (IV-EARN) and cash flow (IV-CF) volatilities are estimated as the variance of quarterly earnings and cash flow shocks from Equation (1).

AGE is defined as the number of years a firm has been public based on its CRSP listing. Pastor and Veronesi, (2003) argue that the return volatility of a typical young firm should decline as the firm ages. LEV is financial leverage, measured as total debt (current plus long-term plus other liabilities) divided by the book value of assets. An increase in leverage could amplify the volatility of equity returns (see, e.g., Fischer, 1976; Christie, 1982). Therefore, levered firms are more likely to experience financial distress, suggesting a positive association between stock-return volatility and financial leverage in the cross-section. BM is the book-to-market ratio, calculated as book equity divided by market equity. Book equity is denoted by total assets minus liabilities, plus balance sheet deferred taxes and investment tax credits (if available) minus the book value of preferred stocks.[8] Market equity is the number of common shares outstanding multiplied by the year's closing price. A negative relationship between book-to-market and idiosyncratic return volatility is expected, because firms with high future growth rates are likely to exhibit high stock return idiosyncratic volatility. Shin and Stultz (2000) provide empirical evidence relating Tobin's Q to the variance of equity. Many previous studies (i.e., Malkiel and Xu, 1997) provide evidence that idiosyncratic volatility is highly correlated with firm size. Hence, we control for firm size, measured by the log of total market (common) equity. Return-on-equity (ROE), used as a measure of profitability, is defined as earnings divided by book equity. Wei and Zhang (2006) show that a declining return-on-equity contributes to the upward trend in idiosyncratic volatility. Dividend yield (DY) is the value of dividends divided by market equity. Pastor and Veronesi (2003) find that idiosyncratic return volatility tends to be higher for firms that pay no dividends. By contrast, Liu et al. (2014) show that the dividend yield is positively related to idiosyncratic volatility and attributes it to the increase in leverage after making dividend payment out of liabilities. Finally, stock illiquidity (ILLIQ) is measured in the spirit of the return-to-volume measure of Amihud (2002). Specifically, for each stock in each year, the illiquidity measure is given by:

$$\mathrm{ILLIQ}_{KT} = \frac{1}{T}\sum_{s=1}^{T}\frac{|\mathrm{R}_{KS}|}{VOLD_{KS}} \qquad (8)$$

where $|\mathrm{R}_{KS}|$ is the absolute return for stock k for month s during year T and $VOLD_{ks}$ is the dollar trading volume of stock k for month s.

Table 4, Panel A, presents descriptive statistics. The mean and median values of LOG (IV-GTFP)-3, 4 and 5 are around .046 and .01, respectively, with a high standard deviation relative to the

[8] Depending on availability, I use redemption, liquidation, or par value (in this order) to estimate the book value of preferred stock.

magnitude of the mean or median. The median book-to-market is 0.64, a value lower than 1, indicating that the average firm in the sample is a firm recording growth. However, the mean book-to-market is greater (the value is around 1) due to the influence of a few outliers with values above 100. The mean value of financial leverage is .48 and the mean size, measured in logarithm, is 19.09. Finally, the mean return on equity, dividend yield and illiquidity measure are .54%, 2.6% and 3.03 respectively. Panel B reports the Pearson correlations between the independent variables employed in Equation (7). The table shows that the volatilities of productivity-related variables (IV-GTFP-3, IV-GTFP-4, and IV-GTFP-5) are, not surprisingly, all positively correlated. Size and age are negatively correlated with idiosyncratic productivity volatility, similar to the negative relationship documented in the literature between idiosyncratic return volatility and firm size and age. As expected, earnings and cash flows volatilities are positively associated with each other (i.e., more profitable firms have higher cash flow) and with productivity volatility. The correlation matrix shows that age is positively correlated with size, indicating that mature firms have larger size than young ones. Finally, the propensity to pay dividends increases with an increase in firm age, leverage, and book-to-market, and decreases with an increase in size.

<Insert Table 4>

Table 5 shows the regression results from Equation (7). As before, all regressions use the GMM procedure with Newey and West (1987) correction for auto correlation. we find qualitatively similar results when using Yule–Walker regression and thus do not report them.

<Insert Table 5>

The results that firm-level idiosyncratic volatility has increased over time are consistent with the evidence from the aggregate time-series regressions reported earlier. However, the increase in idiosyncratic volatility is less pronounced than in the aggregate results. The TIME coefficient is around .001 (.01) and significant at the 1% level in all idiosyncratic TFP growth, GTFP, (idiosyncratic return) volatility specifications, columns 1–3 (4–9) indicating an upward trend in idiosyncratic volatility.

For specifications 4–9, the relationship between idiosyncratic return and productivity volatilities is examined, including control variables such as earnings and cash flow volatility. The dependent variable in regression specifications 4, 6, and 8 is the firm-level return idiosyncratic volatility in year t computed using daily returns, while the variable in regression specifications 5, 7, and 9 is the idiosyncratic volatility computed using monthly returns. Since the TIME variable remains statistically significant after including GTFP volatility, this in no way precludes other theories of firm-specific returns variation. Therefore, my results do not fully explain the increase in idiosyncratic return volatility.

We find that the coefficient estimate for idiosyncratic TFP growth volatility is strongly positive and nearly has the same value whether we use daily or monthly returns in calculating volatility (Log IV-GTFP-5, IV-GTFP-4 and IV-GTFP-3 coefficient estimates are approximately .7, .65, and .56, respectively). To indicate temporal causality between idiosyncratic productivity and return volatilities, the results should show two facts. First, the two volatilities should have increased over time. Both the time-series and panel regression document that the time-series variation in idiosyncratic return and productivity growth volatilities has been increasing over the sample period. Second, there should be evidence that idiosyncratic productivity growth volatility "causes" the idiosyncratic return volatility. This evidence has been also confirmed through time-series and panel regression. Therefore, the results show the power of TFP growth volatility in explaining the trend in idiosyncratic return volatility. A reader could argue for adding an interaction term of a TIME with GTFP volatility as a direct test of whether the GTFP volatility plays a role in explaining the time trend of idiosyncratic return volatility. However, this is not correct as adding the interaction term in the regression tests for the time varying impact of a unit change in the volatility of GTFP on the idiosyncratic return volatility. This argument is not related to the main premise of this study that the temporal increase in the GTFP volatility coupled with a significant impact of it on return volatility has a significant impact on the upward trend of idiosyncratic return volatility. To further examine this point, let us begin with the result that GTFP volatility has an impact on idiosyncratic return volatility, represented by a positive B1 in Equation (9):

$$\text{Log}\ (\text{IV-RET}_{it}) = \beta 0 + \beta 1\ \text{Log}\ (\text{IV-GTFP}_{it}) + \varepsilon_{it} \qquad (9)$$

If the impact of GTFP volatility on the idiosyncratic return volatility increases over time, B1 can be written as a function of TIME:

$$\beta 1 = \alpha 0 + \alpha 1 \text{TIME}_t + \psi_{it} \qquad (10)$$

Substituting (9) into (10) yields the following model specification:

$$\text{Log}\ (\text{IV-RET}_{it}) = \beta 0 + \alpha 0\ \text{Log}\ (\text{IV-GTFP}_{it}) + \alpha 1 \text{TIME}_t * \text{Log}\ (\text{IV-GTFP}_{it}) + \text{Log}\ (\text{IV-GTFP}_{it}) * \psi_{it} + \varepsilon_{it} \qquad (11)$$

Given that the interaction term "TIME * Log (IV-GTFP)" is derived from Equation (10), the coefficient on the interaction term indicates how the impact of GTFP on idiosyncratic return volatility varies over time. However, this is not the key hypothesis in this paper.

The coefficients of the control variables are as expected. Volatility indeed tends to be higher for younger than for older firms, as the age coefficient is negative, indicating that, over time, as firms become larger and more mature, their idiosyncratic volatility decreases. High-leverage firms tend to have high idiosyncratic volatility. Levered firms are assumed to have a higher bankruptcy risk and, hence, higher return volatility. Idiosyncratic volatility is negatively related to stock illiquidity, as measured by the return-to-volume measure of Amihud (2002).

Since idiosyncratic volatility is unobservable and model dependent, we also apply the factor model in a decomposing total volatility utilizing the CAPM model and a measure of idiosyncratic variance from Fama and French's (2015) five-factor model.

5. Robustness

5.1. Idiosyncratic Volatility from a Factor Model

The tests hitherto used the beta-free method of the single factor CAPM of Campbell et al. (2001). While the tests were deemed appropriate at the aggregate level because they avoid having to calculate a large number of betas, they become important when estimating idiosyncratic volatility at the firm level.

Idiosyncratic returns are constructed within each calendar year T by estimating a factor model using all observations within the year. The factor models take the form:

$$R_{it} = \gamma_{0i} + \acute{y}\,\mathbf{F}_t + \varepsilon_{it} \qquad (12)$$

where t denotes a daily or monthly observation. Idiosyncratic volatility is then calculated as the variance of residuals ε_{it} within the calendar year. The result of this procedure is a panel of firm-year idiosyncratic volatility estimates. The first return factor model is the market model, specifying F_t as the return on the CRSP equal weighted market portfolio. The second model specifies F_t as the 5 x 1 vector of Fama and French (2015) factors. A firm-year observation is included if the stock has no missing daily (monthly) returns within the year.

Table 6 reports the main results. As before, all the regressions are estimated using the GMM and the t-statistics are computed using the heteroscedasticity- and autocorrelation-consistent standard errors of Newey and West (1987). The dependent variable is the annual idiosyncratic volatility estimated from daily returns, as shown in the first three columns, and idiosyncratic volatility estimated from monthly returns, as shown in the last three columns. As previously, control variables are financial leverage, book-to-market, size, age, ROE, dividend yield, firm illiquidity, and profit volatility (earnings and cash flow). The results estimated from the factor model are still consistent with the earlier tests. we find that the stock fundamentals of TFP volatility play a role in explaining idiosyncratic return volatility estimated from the single factor model. Particularly, the coefficients are LOG (IV-GTFP)-5 = .686 (.707), LOG (IV-GTFP)-4 =.6337 (.6611), and LOG (IV-GTFP)-3 = .556 (.588) when using daily (monthly) observations with 1% significance. The results are statistically significant if we use the Fama and French (2015) factor model: LOG (IV-GTFP)-5 = .672 (.679), LOG (IV-GTFP)-4 = .621 (.634), and LOG (IV-GTFP)-3 = .545 (.577) when using daily (monthly) observations with 1% significance. Thus, the results are similar regardless of the factor model used to estimate the idiosyncratic volatility. The results also verify that the trend in return volatility is increasing over time, as the coefficient of TIME is positive and statistically significant. Overall, the evidence in Tables 6 and 5 supports the hypothesis that the positive trend in idiosyncratic volatility documented in previous studies is influenced by changes in firm fundamentals, namely, the TFP.

<Insert Table 6>

The control variables have the expected signs. Large firms tend to have smaller idiosyncratic volatility. The coefficient of financial leverage is positive and highly significant. This is consistent with the leverage effect, where stockholders bear a greater share of the total cash flow risk of the firm and stock return volatility increases accordingly. The results also show that idiosyncratic volatility is negatively associated with age. The volatility of firm profits (measured by earnings and cash flow) accounts for some of the volatility in firm's idiosyncratic return. Particularly, the coefficient of LOG (IV-EARN) and LOG (IV-CF) volatility is around.02 (.04), .11 (.1) using the daily (monthly) to estimate idiosyncratic return volatility, respectively. Among volatility measures (productivity, earning and cash flow), the productivity variable has the strongest coefficient estimate (i.e., .68 versus .02 and .11 of earnings and cash flow volatility, respectively). Additionally, the productivity variable is statistically significant at the 1% level, even after controlling for the effects of both earnings and cash flow volatility. Overall, the evidence from the factor-model regressions is consistent with that obtained earlier, in that the increase in idiosyncratic productivity growth volatility over time plays a role in explaining the trend in idiosyncratic return volatility.

5.2. Firm Fixed Effects Analysis

There could be a concern that inferences about the association between time trends and the volatilities of returns and productivity growth are caused by firm fixed effects. While the Newey and West (1987) autocorrelation correction mitigates such concerns, we examine the robustness of the results by estimating fixed effect regression. The results (unreported) from the fixed-effects model suggest that the positive coefficients of TIME and TFP growth (GTFP) volatility are robust.

6. Conclusions

In this paper, we address the issue of the increasing average idiosyncratic volatility in stock returns, previously documented by Campbell et al. (2001). This apparent rise in idiosyncratic volatility became an actively researched area in asset pricing, with studies proposing different explanations for the idiosyncratic return volatility puzzle; however, this study provides new evidence that explains both the increase in idiosyncratic return volatility and the idiosyncratic fundamental cash flow variability.

While Irvine and Pontiff (2009) show that increasing competition can increase the variability of fundamental cash flows and earnings, thereby increasing idiosyncratic volatility, the variability of these fundamentals partly comes from changes in total factor productivity (TFP). Idiosyncratic TFP growth rate (GTFP) volatility is also significantly related to the return variance in time series and cross-section. Showing that GTFP volatility plays an important role in explaining the trend of firm-specific risk leads to the question of why there is a widespread increase in the GTFP volatility. The results also rule out the possibility that these findings are explained entirely by cash flow and earnings variability, size, growth, leverage, firm profitability, firm age, dividend yield, and stock illiquidity.

A limitation of this study is that it does not necessarily provide an explanation for relatively short-period return volatilities, as the analysis is limited to annual volatility measures, given that the idiosyncratic TFP variable is only available on an annual basis. An appealing area for future research is examining the time-varying relationship between R&D intensity and expected returns, as the findings imply that idiosyncratic risk, which shows an association with expected return, as documented by several studies (i.e., Fu, 2009; Goyal and Santa-Clara, 2003), has been increasing over time for high-R&D and high-tech firms.

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Table 1: Descriptive Statistics

Panel A presents the basic statistics for the five volatility variables. The five volatility variables are the natural log of annual idiosyncratic variance estimated from daily stock returns [LOG(IV_RET)_daily], monthly stock returns [LOG(IV_RET)_monthly], quarterly earnings [LOG(IV_EARN)], quarterly cash-flows [LOG(IV_CF)], and annual TFP growth rate [LOG(IV_GTFP)], using firm level data.

Panel B presents the correlation coefficients between the five volatility variables. The p-values are shown below their correlation values.

	LOG(IV-RET)-daily	LOG(IV-RET)-monthly	LOG(IV-EARN)	LOG(IV-CF)	LOG(IV-GTFP)
Number of observations	50	50	50	50	50
Mean	-1.4030	-2.6187	0.8973	1.1653	0.0768
Std Dev	0.6065	0.6380	0.7230	0.4907	0.0412
Minimum	-2.9303	-4.7367	-0.8968	-0.1569	0.0092
Lower Quartile	-1.7831	-2.8502	0.7795	1.0786	0.0413
Median	-1.5851	-2.6431	1.0603	1.2251	0.0790
Upper Quartile	-0.8896	-2.2753	1.2350	1.3994	0.1001
Maximum	-0.3226	-1.4612	2.4079	2.4099	0.1563

	LOG(IV-RET)-daily	LOG(IV-RET)-monthly	LOG(IV-EARN)	LOG(IV-CF)	LOG(IV-GTFP)
LOG(IV-RET)- daily					
LOG(IV-RET)- monthly	0.9004				
	<.0001				
LOG(IV-EARN)	0.5299	0.6186			
	<.0001	<.0001			
LOG(IV-CF)	0.2745	0.3354	0.8906		
	0.0537	0.0173	<.0001		
LOG(IV-GTFP)	0.7077	0.7714	0.7313	0.5505	
	<.0001	<.0001	<.0001	<.0001	

Table 2: Trend Regression

This table reports linear trend regressions for examining the behavior of annual log of aggregate idiosyncratic volatility (IV) estimated from daily stock returns [LOG(IV_RET)_daily], monthly stock returns [LOG(IV_RET)_monthly], quarterly earnings [LOG(IV_EARN)], quarterly cash-flows [LOG(IV_CF)], and annual TFP growth rate [LOG(IV_GTFP)], using firm level data. Panel A runs the ordinary least squares regression that reports the generalized method of moments-based t-ratio using the Newey–West type of adjustment for autocorrelation and conditional heteroscedasticity. Panel B applies the Yule–Walker method regression, which also accounts for autocorrelation. TIME is a time trend variable that takes values from 1 to 50 for each of the years from 1964 to 2013.The number of observations in both panels is 50. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: OLS Estimates		
	Constant	TIME
LOG(IV-RET)- daily	-1.9796***	0.0226**
	[-8.17]	[2.20]
LOG(IV-RET)- monthly	-3.3349***	0.027**
	[-11.12]	[2.46]
LOG(IV-EARN)	-0.1333	0.0404***
	[-0.43]	[4.8]
LOG(IV-CF)	0.606***	0.0219***
	[3.41]	[4.48]
LOG(IV-GTFP)	0.0157**	0.0024***
	[2.25]	[7.46]

Panel B: Yule-Walker Estimates	Constant	TIME
LOG(IV-RET)- daily	-2.0482***	0.0241**
	[-7.41]	[2.56]
LOG(IV-RET)- monthly	-3.376**	0.0284***
	[-14.05]	[3.47]
LOG(IV-EARN)	-0.1269	0.041***
	[-0.55]	[5.08]
LOG(IV-CF)	0.6266***	0.0215***
	[3.64]	[3.71]
LOG(IV-GTFP)	0.0157*	0.0024***
	[1.84]	[8.27]

Table 3: Two-step Trend Regression

This table shows the results for the time-series regressions of the residuals of idiosyncratic return variance, where the idiosyncratic variance (IV) is estimated either from daily return [LOG(IV-RET)-daily] in Panel A or from monthly return [LOG(IV-RET)-monthly] in Panel B, on a time trend (step 2: a) or on a time trend and cash flow volatility [LOG(IV-CF)] , earnings volatility [LOG(IV-EARN)], or idiosyncratic TFP growth rate volatility [LOG(IV-GTFP)] (step 2:b). We use the generalized method of moments to estimate the model. The t-statistics (in parentheses) are calculated using Newey and West's (1987) heteroscedasticity and autocorrelation-consistent standard errors. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Daily return

Step 1	Step 2: a			OR	Step 2:b				
LOG(IV-RET)t = β0 + β1LOG(IV-EARN)t + et	et =a0 +a1TIMEt	a0	a1		et =a0 +a1TIME+ a2LOG(IV-CF)+ a3*LOG(IV-GTFP)	a0	a1	a2	a3
		-0.1184	0.0046			0.0464	-0.0109	-0.5767***	11.772***
		[-0.66]	[0.55]			[0.23]	[-0.77]	[-3.58]	[3.11]
Step 1	Step 2: a				Step 2:b				
LOG(IV-RET)t = β0 + β1LOG(IV-CF)t + et	et =a0 +a1TIMEt	-0.3868*	0.0152	OR	et =a0 +a1TIME+ a2LOG(IV-EARN)+ a3*LOG(IV-GTFP)	-0.6110***	-0.0118	-0.1199	13.2703***
		[-1.72]	[1.52]			[-3.32]	[-0.74]	[-0.77]	[3.34]

Panel B: Monthly return

Step 1	Step 2: a				Step 2: b				
LOG(IV-RET)t = β0 + β1LOG(IV-EARN)t + et	et =a0 +a1TIMEt	-0.1265	0.0050	OR	et =a0 +a1TIME+ a2LOG(IV-CF)+ a3*LOG(IV-GTFP)	0.0755	-0.0101	-0.6503***	12.2341***
		[-0.68]	[0.58]			[0.40]	[-0.87]	[-6.01]	[3.26]
Step 1	Step 2: a				Step 2:b				
LOG(IV-RET)t= β0 + β1LOG(IV-CF)t + et	et =a0 +a1TIMEt	-0.4453*	0.0175	OR	et =a0 +a1TIME+ a2LOG(IV-EARN)+ a3*LOG(IV-GTFP)	-0.6792***	-0.0116	-0.1093	13.9751***
		[-1.72]	[1.64]			[-3.01]	[-0.89]	[-0.73]	[3.40]

Table 4: Correlation Between Control Variables

The table reports the Pearson correlations among the idiosyncratic productivity growth variables [LOG (IV-GTFP)-3, LOG (IV-GTFP)-4, LOG (IV-GTFP)-5, where 3,4 and 5 indicate three, four and five years of observations respectively] and control variables in the study. The control variables include firm age, financial leverage (FL), book-to-market ratio (BM), firm size, return on equity (ROE), dividend yield (DY), and stock illiquidity (ILLIQ), idiosyncratic cash flow [LOG(IV-CF)] and earnings [LOG(IV-EARN)] volatilities. The p-values are below their correlation values, with values less than 0.10, 0.05, and 0.01 indicating significance at the 10%, 5%, and 1% levels, respectively. we construct the volatility measures of idiosyncratic TFP growth rate, earnings and cash flow by finding the time-series variance of these fundamentals. The earnings and cash flow volatilities are estimated on an annual basis using the quarterly earnings and cash flow shocks in a year from Equation (1).

Panel A

	LOG (IV-GTFP)-3	LOG (IV-GTFP)-4	LOG (IV-GTFP)-5	AGE	FL	BM	Size	ROE	DY	ILLIQ	LOG(IV-EARN)	LOG(IV-CF)
Number of observations	82,864	73,213	64,950	108,356	106,665	107,676	108,149	98,100	108,03	108,356	103,398	53,286
Mean	0.0460	0.0469	0.0475	16.5027	0.4831	1.0027	19.0936	0.0054	0.0266	3.0306	-2.6579	0.4688
Std Dev	0.1839	0.1613	0.1479	15.2465	0.2435	57.4707	2.2370	7.1909	1.9827	2.3849	2.2023	0.8888
Lower Quartile	0.0023	0.0035	0.0044	6	0.3283	0.3703	17.4405	0.0037	0.0000	1.6350	-4.1237	0.0000
Median	0.0076	0.0100	0.0118	12	0.4709	0.6431	18.9747	0.0235	0.0038	2.1426	-2.8207	0.6931
Upper Quartile	0.0256	0.0301	0.0333	22	0.6091	1.0793	20.5906	0.0421	0.0264	4.2217	-1.3619	1.1787

Panel B	LOG (IV-GTFP)-3	LOG (IV-GTFP)-4	LOG (IV-GTFP)-5	AGE	FL	BM	Size	ROE	DY	ILLIQ	LOG(IV-EARN)	LOG(IV-CF)
LOG (IV-GTFP)-4	0.8534											
	<.0001											
LOG (IV-GTFP)-5	0.7748	0.8869										
	<.0001	<.0001										
AGE	-0.0743	-0.0825	-0.0884									
	<.0001	<.0001	<.0001									
FL	-0.0029	-0.0047	-0.0069	0.0465								

	0.4138	0.2107	0.0793	<.0001							
BM	-0.0009	-0.0011	-0.0012	0.0021	-0.0181						
	0.7942	0.7694	0.7533	0.5011	<.0001						
Size	-0.0464	-0.0516	-0.0538	0.3291	-0.0709	-0.0189					
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001					
ROE	0.0069	0.0068	0.0053	-0.0037	-0.0082	0.0001	0.0025				
	0.0546	0.0766	0.1886	0.2446	0.0106	0.9782	0.4275				
DY	-0.0009	-0.0010	-0.0013	0.0067	0.0058	0.9902	-0.0145	0.0003			
	0.7908	0.7795	0.7368	0.0287	0.0578	<.0001	<.0001	0.9245			
ILLIQ	-0.0203	-0.0247	-0.0291	-0.0326	0.0382	0.0016	-0.2125	0.0004	0.0005		
	<.0001	<.0001	<.0001	<.0001	<.0001	0.6103	<.0001	0.9087	0.8681		
LOG(IV-EARN)	0.1075	0.1072	0.1064	0.1602	0.1834	-0.0081	0.1676	0.0000	0.0208	-0.0700	
	<.0001	<.0001	<.0001	<.0001	<.0001	0.0092	<.0001	0.9949	<.0001	<.0001	
LOG(IV-CF)	0.0168	0.0188	0.0209	0.0998	0.0560	-0.0217	0.2993	0.0024	0.0047	-0.0295	0.1035
	0.0004	0.0002	<.0001	<.0001	<.0001	<.0001	<.0001	0.5865	0.2741	<.0001	<.0001

Table 5: Firm-Level Regressions

This table reports the results of the panel regressions of the logarithm of idiosyncratic TFP growth volatility [LOG (IV-GTFP)] on time trend (columns 1-3) and panel regressions of the idiosyncratic return variance on time trend, [LOG (IV-GTFP)], and control variables (columns 4-9). Idiosyncratic variance (IV) of return is estimated either from daily return [LOG(IV-RET)-daily] or from monthly return [LOG(IV-RET)-monthly].The control variables, measured at the end of the previous time period, include firm age, financial leverage (FL), book-to-market ratio (BM), firm size, return on equity (ROE), dividend yield (DY), and stock illiquidity (ILLIQ). The table also controls for idiosyncratic earnings [LOG (IV-EARN)] and cash flow volatility [LOG (IV-CF)]. The (IV-GTFP) is calculated from the annual idiosyncratic TFP growth rate (GTFP) using three, four or five observations from year t to year t-2, t-3 or t-4 (IV-GTFP-3, 4 or 5). The earnings and cash flow volatilities are estimated on an annual basis using the quarterly earnings and cash flow shocks from Equation (1). TIME is a time trend variable that takes values from 1 to 50 for each of the years from 1964 to 2013. The t-statistics (in parentheses) are calculated using Newey and West's (1987) heteroscedasticity and autocorrelation-consistent standard errors. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	1	2	3	4	5	6	7	8	9
	LOG (IV-GTFP)-5	LOG (IV-GTFP)-4	LOG (IV-GTFP)-3	LOG (IV-RET)-daily	LOG (IV-RET)-monthly	LOG (IV-RET)-daily	LOG (IV-RET)-monthly	LOG (IV-RET)-daily	LOG (IV-RET)-monthly
Intercept	0.0096***	0.0100***	0.0101***	2.9034***	1.3582***	2.9940***	1.4172***	3.0955***	1.5205***
	[4.66]	[5.18]	[5.51]	[32.53]	[15.85]	[34.82]	[17.24]	[37.42]	[19.27]
TIME	0.0012***	0.0012***	0.0012***	0.0109***	0.0097***	0.0114***	0.0103***	0.0119***	0.0105***
	[16.23]	[17.03]	[17.51]	[15.68]	[13.98]	[16.65]	[15.14]	[17.77]	[15.88]
LOG (IV-GTFP)-5				0.7007***	0.6932***				
				[13.69]	[12.81]				
LOG (IV-GTFP)-4						0.6485***	0.6542***		
						[13.36]	[12.38]		
LOG (IV-GTFP)-3								0.5681***	0.5812***
								[13.76]	[12.57]
AGE				-0.0079***	-0.0079***	-0.0087***	-0.0087***	-0.0096***	-0.0096***
				[-16.83]	[-17.22]	[-18.93]	[-19.32]	[-21.36]	[-21.77]

FL				0.4961***	0.5883***	0.4744***	0.5505***	0.4465***	0.5052***
				[12.96]	[15.63]	[13.05]	[15.33]	[13.15]	[14.96]
BM				-0.002	-0.00025	-0.0047	-0.0022	-0.0081	-0.00527
				[-0.27]	[-0.03]	[-0.69]	[-0.33]	[-1.26]	[-0.82]
Size				-0.2625***	-0.19807***	-0.26551***	-0.1994***	-0.2688***	-0.2015***
				[-62.09]	[-49.18]	[-65.24]	[-51.41]	[-69.01]	[-54.2]
ROE				0.0013	0.0002	0.0010	0.0001	0.0007	-0.0002
				[1.14]	[0.21]	[0.86]	[0.06]	[0.57]	[-0.18]
DY				-0.0221	-0.0804	-0.0615	-0.1113	-0.0958	-0.1394
				[-0.25]	[-0.98]	[-0.65]	[-1.29]	[-1.01]	[-1.62]
ILLIQ				-0.0318***	-0.0225***	-0.0307***	-0.0213***	-0.0303***	-0.0223***
				[-13.58]	[-9.61]	[-13.51]	[-9.50]	[-13.72]	[-10.26]
LOG(IV-EARN)				0.0234***	0.0387***	0.0218***	0.0376***	0.0195***	0.0358***
				[8.24]	[13.20]	[7.89]	[13.35]	[7.29]	[13.19]
LOG(IV-CF)				0.1220***	0.1141***	0.1187***	0.1118***	0.1168***	0.1103***
				[20.03]	[18.23]	[20.30]	[18.48]	[20.74]	[18.94]
Number of observations	64,950	73,213	82,864	34,836	34,836	38,202	38,202	41,944	41,944

Table 6: Firm-Level Regressions Using a Factor Model

The dependent variable is the idiosyncratic firm return variance, estimated either from daily or monthly returns. we apply the factor model in calculating idiosyncratic return volatility utilizing CAPM model (Panel A) and a measure of idiosyncratic variance from Fama and French's (FF, 2015) five-factor model (Panel B). Idiosyncratic returns are constructed within each calendar year by estimating these factor models using all observations (daily or monthly) within the year. The t-statistics (in parentheses) are calculated using Newey and West's (1987) heteroscedasticity and autocorrelation-consistent standard errors. The control variables, measured at the end of the previous time period, include firm age, financial leverage (FL), book-to-market ratio (BM), firm size, return on equity (ROE), dividend yield (DY), and stock illiquidity (ILLIQ). The table also controls for idiosyncratic earnings [LOG (IV-EARN)] and cash flow [LOG (IV-CF)] volatility. The (IV-GTFP) is calculated from the annual idiosyncratic TFP growth rate (GTFP) using three, four or five observations from year t to year t-2, t-3 or t-4 (IV-GTFP-3, 4 or 5). The earnings and cash flow volatilities are estimated on an annual basis using the quarterly earnings and cash flow shocks from Equation (1). TIME is a time trend variable that takes values from 1 to 50 for each of the years from 1964 to 2013.

Panel A : single factor

	LOG (IV-RET)-daily	LOG (IV-RET)-daily	LOG (IV-RET)-daily	LOG (IV-RET)-monthly	LOG (IV-RET)-monthly	LOG (IV-RET)-monthly
Intercept	-2.2326***	-2.1526***	-2.0365***	-0.7381***	-0.6738***	-0.5720***
	[-23.78]	[-23.59]	[-23.36]	[-7.83]	[-7.52]	[-6.66]
TIME	0.0103***	0.0107***	0.0110***	0.0121***	0.0125***	0.0127***
	[14.54]	[15.31]	[16.11]	[16.37]	[17.39]	[18.06]
LOG (IV-GTFP)-5	0.6866***			0.7069***		
	[13.42]			[12.49]		
LOG (IV-GTFP)-4		0.6337***			0.6611***	
		[13.2]			[12.59]	
LOG (IV-GTFP)-3			0.5562***			0.5888***
			[13.57]			[12.64]
AGE	-0.0089***	-0.0097***	-0.0106***	-0.0093***	-0.0100***	-0.0109***
	[-18.43]	[-20.62]	[-22.95]	[-18.54]	[-20.56]	[-22.89]
FL	0.4860***	0.4628***	0.4329***	0.5909***	0.5464***	0.4972***
	[12.57]	[12.58]	[12.66]	[14.9]	[14.44]	[14.02]

BM	-0.0001	-0.0008	-0.0048	0.0020	-0.0003	-0.0037
	[-0.02]	[-0.09]	[-0.64]	[0.24]	[-0.03]	[-0.51]
Size	-0.2814***	-0.2837***	-0.2873***	-0.2282***	-0.2295***	-0.2314***
	[-64.81]	[-67.48]	[-71.61]	[-51.79]	[-54.43]	[-57.28]
ROE	0.0006	0.0003	0.0000	0.0001	-0.0001	-0.0005
	[0.46]	[0.25]	[0.04]	[0.08]	[-0.1]	[-0.36]
DY	-0.0162	-0.0449	-0.0816	-0.0633	-0.0974	-0.1262
	[-0.17]	[-0.45]	[-0.83]	[-0.68]	[-0.99]	[-1.31]
ILLIQ	-0.0354***	-0.0343***	-0.0339***	-0.0285***	-0.0270***	-0.0279***
	[-14.92]	[-14.87]	[-15.23]	[-11.1]	[-10.97]	[-11.75]
LOG(IV-EARN)	0.0241***	0.0226***	0.0205***	0.0458***	0.0445***	0.0423***
	[8.35]	[8.07]	[7.62]	[14.71]	[14.84]	[14.72]
LOG(IV-CF)	0.1144***	0.1117***	0.1102***	0.1026***	0.1017***	0.1005***
	[18.65]	[18.77]	[19.25]	[15.3]	[15.75]	[16.2]
Number of observations	34,104	37,365	41,006	34,822	38,187	41,927

Panel B : FF 2015 factor

	LOG (IV-RET)-daily	LOG (IV-RET)-daily	LOG (IV-RET)-daily	LOG (IV-RET)-monthly	LOG (IV-RET)-monthly	LOG (IV-RET)-monthly
Intercept	-2.1586***	-2.0751***	-1.9564***	-1.3562***	-1.3011***	-1.2017***
	[-23.07]	[-22.79]	[-22.49]	[-13.95]	[-14.01]	[-13.56]
TIME	0.0101***	0.0105***	0.0109***	0.0143***	0.0149***	0.0151***
	[14.31]	[15.09]	[15.92]	[18.57]	[19.91]	[20.63]
LOG (IV-GTFP)-5	0.6724***			0.6791***		
	[13.32]			[11.66]		

LOG (IV-GTFP)-4		0.6213***			0.6340***	
		[13.05]			[11.42]	
LOG (IV-GTFP)-3			0.5454***			0.5778***
			[13.3]			[12.29]
AGE	-0.0090***	-0.0098***	-0.0106***	-0.0096***	-0.0102***	-0.0111***
	[-18.72]	[-20.89]	[-23.23]	[-18.49]	[-20.3]	[-22.64]
FL	0.5142***	0.4889***	0.4576***	0.5638***	0.5144***	0.4730***
	[13.14]	[13.07]	[13.18]	[14.16]	[13.5]	[13.26]
BM	0.0009	0.0003	-0.0037	0.0000	-0.0022	-0.0056
	[0.11]	[0.03]	[-0.5]	[.01]	[-0.28]	[-0.77]
Size	-0.2888***	-0.2913***	-0.2950***	-0.2322***	-0.2334***	-0.2354***
	[-67.21]	[-69.96]	[-74.24]	[-51.07]	[-53.53]	[-56.56]
ROE	0.0007	0.0004	0.0001	0.0002	0.0001	-0.0002
	[0.51]	[0.31]	[0.1]	[0.1]	[0.05]	[-0.11]
DY	-0.0080	-0.0371	-0.0736	-0.0954	-0.1277	-0.1611*
	[-0.09]	[-0.37]	[-0.75]	[-1.08]	[-1.38]	[-1.75]
ILLIQ	-0.0331***	-0.0320***	-0.0317***	-0.0341***	-0.0324***	-0.0332***
	[-13.98]	[-13.92]	[-14.27]	[-12.22]	[-12.06]	[-12.87]
LOG(IV-EARN)	0.0233***	0.0218***	0.0197***	0.0454***	0.0451***	0.0430***
	[8.09]	[7.79]	[7.33]	[14.02]	[14.45]	[14.34]
LOG(IV-CF)	0.1120***	0.1096***	0.1081***	0.0976***	0.0962***	0.0963***
	[18.3]	[18.47]	[18.93]	[13.52]	[13.82]	[14.47]
Number of observations	34,104	37,365	41,006	34,822	38,187	41,927

Figure 1. Idiosyncratic Return Volatility from Daily Observations

Figure 1 depicts the annual idiosyncratic return volatility from 1964 to 2013. The series is estimated as the cross-sectional annual variance using daily excess returns (return minus equally weighted market return) within each year.

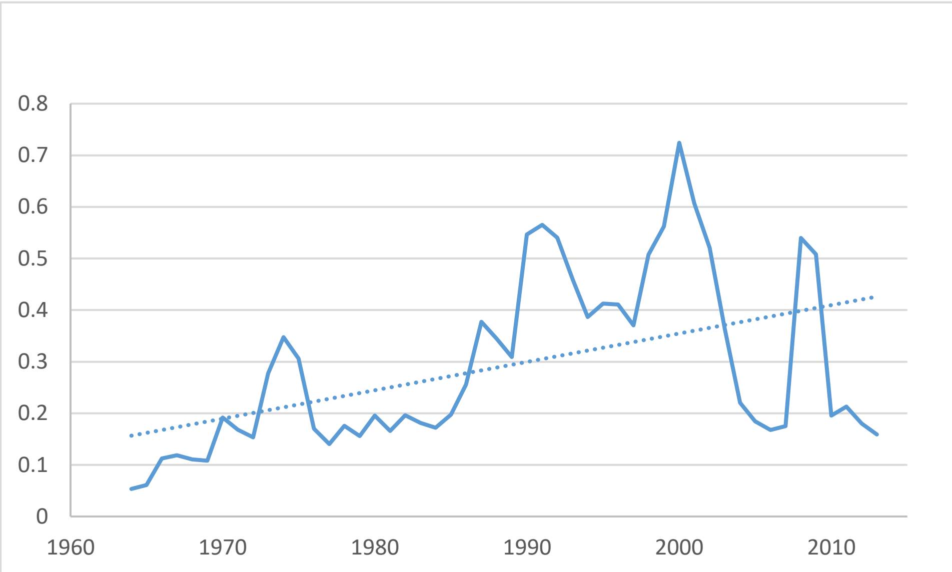

Figure 2. Idiosyncratic Return Volatility from Monthly Observations

Figure 2 depicts the annual idiosyncratic return volatility from 1964 to 2013. The series is estimated as the cross-sectional annual variance using monthly excess returns (return minus equally weighted market return) within each year.

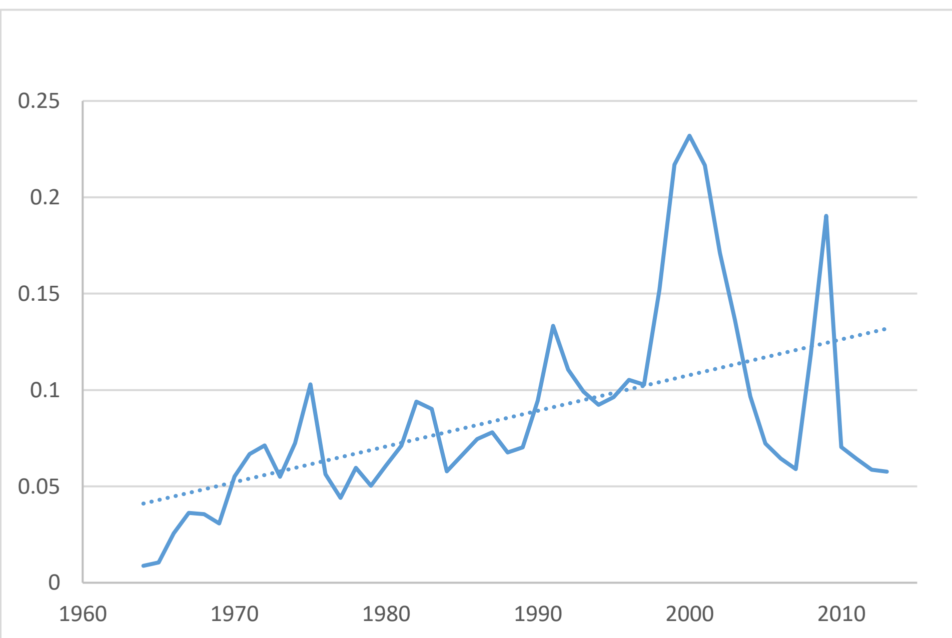

Figure 3. Idiosyncratic Earnings Volatility

Figure 3 depicts the annual idiosyncratic earnings volatility from 1964 to 2013. The series is estimated as the cross-sectional variance of quarterly earning shocks, summed over all four quarters for a year.

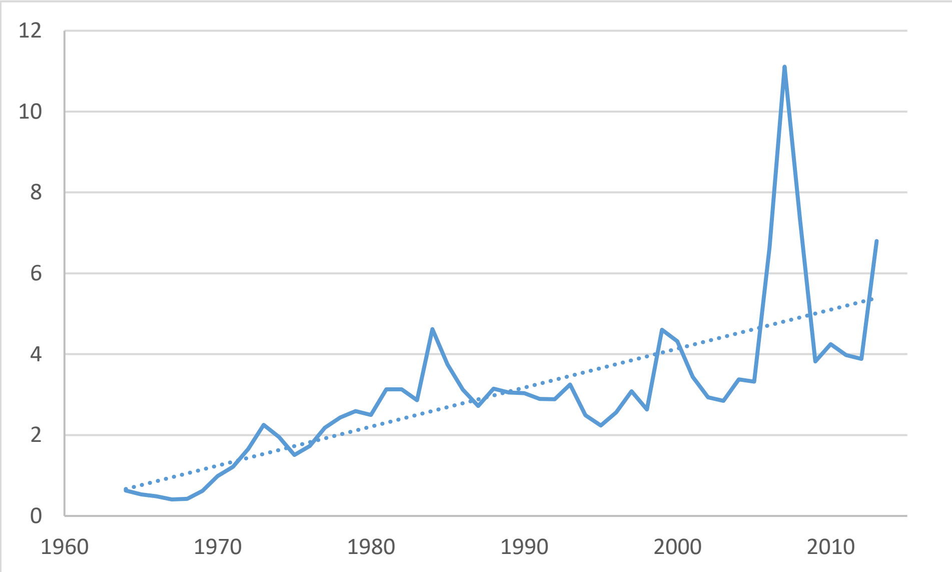

Figure 4. Idiosyncratic Cash Flow Volatility

Figure 4 depicts the annual idiosyncratic cash flow volatility from 1964 to 2013. The series is estimated as the cross-sectional variance of quarterly cash flow shocks, summed over all four quarters for a year.

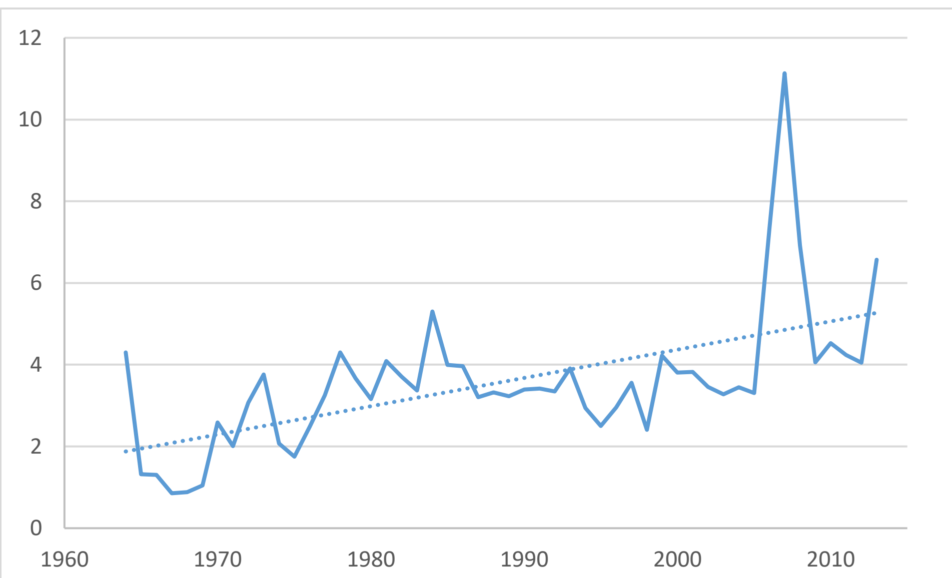

Figure 5. Idiosyncratic TFP Growth Volatility

Figure 5 depicts the annual idiosyncratic total factor productivity growth (GTFP) volatility from 1964 to 2013. The series is estimated as the cross-sectional variance of the annual log TFP change.