# Idiosyncratic Return Volatility, Cash Flows, and Product Market Competition

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Over the past 40 years, the volatility of the average stock return has drastically outpaced total market volatility. Thus, idiosyncratic return volatility has dramatically increased. We estimate this increase to be 6% per year. Consistent with an efficient market, this result is mirrored by an increase in the idiosyncratic volatility of fundamental cash flows. We argue that these findings are attributable to the more intense economy-wide competition. Various cross-sectional and time-series tests support this idea. Economic competitiveness facilitates reinterpretation of the results from the cross-country $R^2$ literature, as well as the US idiosyncratic risk literature. (*JEL* G12, G14).

Idiosyncratic stock-return volatility varies across countries as well as through time. Morck, Yeung, and Yu (2000) focus on cross-country differences in market model return $R^2$s, and show that stock-return $R^2$s are higher in countries with more opaque information environments. Campbell et al. (2001) report that stock-return volatility increased dramatically over the 1962–1997 period, although aggregate market volatility did not change during this time period, implying that the idiosyncratic risk of the typical stock has increased.

In a rational market, stock prices equate to the present value of future-expected cash flows. This basic formulation yields three fundamental explanations for both cross-country differences and the time trend in idiosyncratic risk: (1) discount rate shocks increase idiosyncratic return volatility; (2) cash-flow streams have become more idiosyncratic; or (3) the market is inefficient. The first explanation is not very persuasive, since on theoretical grounds it is questionable whether discount rate news can cause idiosyncratic risk. Discount rate shocks are determined by the true asset pricing model. Modern risk-based asset pricing theories (e.g., Sharpe, 1964) maintain that idiosyncratic risk is not priced, and thus the source of idiosyncratic return variation is not a risk

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factor. Of course, the parameters of the underlying asset pricing model could be subject to idiosyncratic variation that, in turn, causes idiosyncratic shocks to stock returns. For example, in the case of the capital asset pricing model (CAPM), variation in beta could create idiosyncratic changes in discount rates, which are then reflected in idiosyncratic return risk. Since Campbell et al. (2001) examine monthly risk measures using daily data, this explanation seems implausible, since it requires drastic intramonth parameter variation.

The two remaining fundamental explanations are either that idiosyncratic news in cash flows is sufficient to explain the trend of higher idiosyncratic volatility or that the market is inefficient, or both. The first goal of our paper is to examine the US time series of idiosyncratic volatility to assess these explanations. Using various measures of fundamental cash-flow volatility, we find that the trend in idiosyncratic cash-flow volatility mirrors the trend in idiosyncratic stock-return volatility, consistent with market efficiency. Idiosyncratic return volatility forecasts idiosyncratic cash-flow volatility in the following two quarters. This finding leads to another quandary: What has changed in the economy to make firms subject to greater idiosyncratic risk in fundamental cash flows? Our second goal is to investigate explanations for this puzzling trend.

The mosaic of evidence suggests that the recent upward trend in idiosyncratic volatility is related to an increasingly competitive environment in which firms have less market power. When the success of one firm in an industry comes at the expense of another firm in that industry, competition contributes to negative covariance in firm performance. In general, markets reflect an environment with less consumer loyalty to a specific firm, perhaps due to better access to information or the reduction of other search costs. Our results coincide with the findings of economics research that indicates increased competition in the US economy (e.g., Blinder, 2000; London, 2004; and Bils and Klenow, 2004).

Our finding of a relation of between idiosyncratic stock-return volatility and fundamental volatility, as well as our associating this effect with increased competition, provides a new interpretation of evidence from international studies such as Morck, Yeung, and Yu (2000). We recognize that opaque information deters a country's product-market competition. We offer a challenge to the conclusion that information opacity affects stock-return $R^2$s through stock trading. Rather, we argue that information opacity affects a country's fundamental business environment, which in turn affects stock-return $R^2$s.

Our findings offer new evidence on the importance of financial market innovation with regard to economic advancement. Brown and Kapadia (2007) claim that the increase in idiosyncratic risk is related to more volatile firms being listed through initial public offerings, and Bennett and Sias (2006) show that the proportion of firms with small market capitalizations has increased. In light of these studies, our finding of an association between idiosyncratic risk and economic competitiveness leads to an interesting conjecture—financial innovation allows small, risky firms to raise capital, thus inducing greater economy-wide competition.



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The paper is organized as follows. Section 1 describes the sample and discusses our measure of earnings volatility. Section 2 replicates the results of Campbell et al. (2001) for the intersection of firms in the Center for Research in Security Prices (CRSP) and Compustat databases. Section 3 examines the idiosyncratic volatility of earnings, cash flows, and sales over time. Section 4 examines increased competitiveness (including deregulation) as an explanation for increased idiosyncratic volatility, and Section 5 concludes.

## 1. Framework and Data

Since our investigation focuses on the direct link between cash-flow shocks and return volatility, we first outline the link between these two variables with a simple one-period model of stock returns. Specifically,

$$p_0 = \sum_{i=1}^{\infty} \frac{E_0(CF_i)}{(1+k)^i}, \tag{1}$$

where $CF_i$ is the cash flow at time $i$, $k$ is the appropriate discount rate, and $E_0(\cdot)$ is the expectations operator as of time 0. If cash flows follow a random walk, then

$$E_0(CF_i) = CF_0, \quad \forall i \geq 0. \tag{2}$$

Equations (1) and (2) imply that

$$p_0 = \frac{CF_0}{k}. \tag{3a}$$

Similarly,

$$\tilde{p}_1 = \frac{CF_1}{k} = \frac{CF_0 + \tilde{e}_1}{k}. \tag{3b}$$

In this case, $\tilde{e}_1$ is the random unexpected cash-flow shock at time 1. The realized return at time 1 is then a random variable given by

$$\tilde{r}_1 = \frac{\tilde{p}_1 - p_0}{p_0} = \frac{\tilde{e}_1}{kp_0}, \tag{4}$$

with variance

$$\sigma^2(\tilde{r}_1) = \frac{\sigma^2(\tilde{e}_1)}{k^2 p_0^2}. \tag{5}$$

Since $k$ and $p_0$ are predetermined at time 0, the source of the variance of the stock-return process comes directly from the variance of unexpected cash



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flows. This analysis implies that a comparison of cash-flow shock variability to stock market return variability necessitates the use of a cash-flow shock that is scaled by the product of the price and the discount rate.

A recent study by Wei and Zhang (2006) compares idiosyncratic stock market volatility to the volatility of the level of earnings divided by the book value of shareholder equity. This comparison does not directly illustrate the source of cash-flow volatility, since return volatility is determined by unexpected shocks to the cash-flow stream, not by the cash-flow stream itself. Scaling by the book value of equity instead of price adds noise to the variance estimation, the bias or impact of which is unclear. Inference from their results is also impeded by the fact that they present evidence of total rather than idiosyncratic ROE volatility. Comin and Philippon (2005) examine sales growth volatility. Their measure is an improvement on Wei and Zhang (2006) in that they do not scale by book value, although like Wei and Zhang (2006), the idiosyncratic component of risk is left unexamined.

### 1.1 CRSP-Compustat database

Our data come from the intersection of the CRSP/Compustat merged databases. In general, Compustat coverage is a subset of CRSP coverage. We must further limit our data as the persistence in time-series accounting data in our analysis of idiosyncratic cash-flow shocks requires at least twelve consecutive quarters of Compustat data for each firm in the sample. For each firm, we also require that each quarter have all of the following Compustat data items: sales (2), depreciation and amortization (5), end-of-quarter stock price (14), number of common shares used to calculate earnings per share (15), and earnings per share excluding extraordinary items (19).

The empirical analysis of cash-flow volatility examines three separate cash-flow measures: (i) earnings per share, for which we use Compustat data item 19; (ii) cash flow per share, which we compute by adding depreciation (data item 5) per share to earnings per share; and (iii) sales per share, for which we divide Compustat data item 2 by data item 15. We expect that these three measures should sufficiently reflect any fundamental cash-flow shocks affecting a corporation.

To alleviate the effect of outliers, we winsorize the data. We first divide per-share earnings, cash flows, and sales by price. If the resulting value of any of these three variables is above (below) its respective top (bottom) percentile, we assign to it the value of the observation at the top (bottom) percentile, and then retransform the variable by multiplying by price. This procedure enables us to limit the effect of potentially misleading accounting numbers, without the measurement error sometimes associated with firms with extreme stock-price levels. Table 1 presents winsorized summary information on the sample firms.[1]

[1] In unreported results, we simply delete the outliers instead of winsorizing them and obtain lower point estimates of the growth in idiosyncratic volatility for all cash-flow proxies. Significance of these estimates is similar to that



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**Table 1**
**Univariate sample statistics**

| | $N$ | Mean | $\sigma$ | 25th percentile | Median | 75th percentile |
|---|---|---|---|---|---|---|
| Earnings per share ($) | 577,322 | 0.19 | 0.92 | −0.03 | 0.11 | 0.40 |
| Cash-flow per share ($) | 577,315 | 0.44 | 1.40 | 0.00 | 0.25 | 0.68 |
| Sales per share (million dollars) | 577,315 | 6.35 | 14.96 | 0.70 | 2.84 | 7.30 |
| Earnings-to-price | 577,322 | −0.02 | 0.14 | −0.01 | 0.01 | 0.02 |
| Cash-flow-to-price | 577,315 | 0.01 | 0.12 | 0.00 | 0.02 | 0.04 |
| Sales-to-price | 577,315 | 0.61 | 1.06 | 0.10 | 0.26 | 0.63 |

Aggregate statistics for earnings, cash flow, and sales on the CRSP-Compustat merged database, 1962–2003. If the ratio of any of these three variables divided by price is in the top or bottom 1% of the distribution, the variable is winsorized by setting the price-normalized value equal to the appropriate 1% value and then multiplying by price.

## 1.2 Measuring earnings shocks

Brown and Rozeff (1979), and Brown (1993) report that the levels of accounting measures of cash flows exhibit persistence. To measure the unexpected cash-flow shock correctly in our accounting measures of cash flows, we need to control for the documented persistence in cash flows. A preliminary empirical analysis of our data reveals that all three of our cash-flow measures demonstrate strong time-series persistence. We therefore focus on the differences of these cash-flow variables as the correct measure of innovations in each series. As the residuals of the differences can still exhibit some persistence, as well as seasonal variation, we estimate the following pooled cross-sectional time-series model:

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

This model is estimated at the industry level for each of the 49 Fama-French (1997) industry groups, thus allowing intercepts and slopes to vary depending on the industry. The $E_{it}$ are vectors of either firm-level earnings, cash flows, or sales at quarter $t$. In this model, the residuals $e_{it}$ are vectors of *unexpected* innovations in a firm's cash flow per share. The dependent variable is the difference between the current quarter's earnings and the earnings that were reported in the same quarter of the preceding year.

The primary advantage of the estimation in Equation (6) is that it imposes only limited restrictions on the firm-level residuals. For any particular firm, the unexpected cash-flow innovations do not have to sum to zero, so the model permits a firm to outperform or underperform over time. Also, at any point in time, the cross-sectional vector of unexpected innovations to earnings per share does not have to sum to zero, so the model permits all firms to outperform (underperform) the model's benchmark if economic conditions are particularly strong (weak) in that period.

reported below in Table 3 (earnings and cash-flow idiosyncratic volatility are statistically significant), whereas the trend in idiosyncratic sales volatility is weaker.

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Estimation of Equation (6) requires that up to nine lags of earnings exist in the CRSP-Compustat database. This constraint reduces the sample size from approximately 577,300 firm-specific observations reported in Table 1 to approximately 469,000 firm-specific observations. Due to cross-sectional variation in the number of missing Compustat data items, the reported number of observations is slightly different for earnings, cash flow, and sales.

We use the residuals from Equation (6) to calculate idiosyncratic cash-flow shocks at time $t$. For each firm quarter, we divide its Equation (6) residual by the end-of-quarter stock price in the previous quarter. Ideally, we would also scale earnings by the discount rate as in Equation (4). However, since discount rates must be estimated, scaling by discount rates would introduce noise to our cash-flow shock measures.

### 1.3 Estimation

Using our sample of firms with data in both CRSP and Compustat, we construct a daily equal-weighted index. This index is used to compute monthly total market variance from daily return data. Specifically,

$$\sigma\,(ret)^2_{mt} = \left(\frac{n}{n-1}\right)\sum_{s=1}^{n}(R_{ms} - u_m)^2, \tag{7}$$

where $\sigma^2_{mt}$ is our estimate for monthly variance, $s$ corresponds to days within a month, $n$ is the total number of days in a given month, $R_{ms}$ is the daily return of the equal-weighted market index, and $u_m$ is the average daily return of the index for month $m$. We examine equal-weighted idiosyncratic volatility as opposed to value-weighted idiosyncratic volatility for two reasons. First, if idiosyncratic volatility is caused by trading behavior that is not related to fundamentals, then it should be easier to observe in stocks that have small market capitalizations. These stocks have higher transaction costs, so rational investors will be less likely to induce corrective price pressure (Pontiff, 1996). Second, we are concerned with examining the association between competition and idiosyncratic volatility. Value weighting is less likely to reflect the condition of more competitive companies, since the present value of monopoly rents will be reflected in market values. However, the results (available from the authors) are similar when we use a value-weighted estimation.

Similarly, our monthly idiosyncratic risk measure is estimated from

$$\sigma(ret)^2_{Idio,t} = \frac{1}{j}\left(\frac{n}{n-1}\right)\sum_{i=1}^{j}\sum_{s=1}^{n}(R_{is} - R_{ms})^2, \tag{8}$$

where $j$ is the total number of firms represented in a given month and $n$ is the number of days in a given month. Campbell et al. (2001) show that this measure of idiosyncratic volatility is very close to the idiosyncratic volatility that one can measure from a market model. The advantage of using



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Equation (8) to measure idiosyncratic volatility is that it does not require estimation of beta.

Computation of idiosyncratic cash-flow volatility is analogous. First, we create an equal-weighted index of monthly cash-flow shocks. Because firms' fiscal periods vary, a different sample of firms report quarterly earnings in a particular month. We address nonsynchronicity in the cash-flow reporting by constructing an index that includes cash-flow shocks from the previous month, the current month, and the following month. Therefore, our index is a rolling average of all firms' cash-flow shocks. Denoting the market cash-flow shock index in month $t$ as $e_{mt}$, and the cash-flow shock of firm $i$ at time $t$ as $e_{it}$, a monthly index of the idiosyncratic volatility of cash-flow shocks is constructed as follows:

$$\sigma^2 (CF)_{Idio,t} = \left(\frac{1}{3}\right)\left(\frac{1}{k}\right)\sum_{i=1}^{k}\left(\frac{\pi}{2}\right)(e_{it} - e_{mt})^2, \tag{9}$$

where $k$ is the total number of firms that report earnings at time $t$, time $t-1$, or time $t+1$. Similarly, $e_{it}$ is firm $i$'s cash-flow shock at time $t$. If time $t$ does not correspond to the end of the firm's quarter, $e_{it}$ reflects either the quarterly cash flow that was announced in the previous month or the quarterly cash flow that was announced in the following month. Assuming that $e_{it} - e_{mt}$ has a zero mean, multiplying the squared deviation by $\frac{\pi}{2}$ gives us an estimate of the firm's idiosyncratic volatility at time $t$.[2] Since our earnings data are quarterly and we compare our estimate to monthly stock returns, we multiply our estimate of average idiosyncratic cash-flow risk by 1/3, to produce a monthly estimate. This procedure produces a rolling time-series estimate of monthly fundamental volatility, analogous to Campbell et al.'s (2001) calculation of idiosyncratic return volatility, from January 1964 through December 2003. The resulting time series consists of 480 months of idiosyncratic volatility of earnings, cash flows, and sales.

## 2. Idiosyncratic Return Volatility in the CRSP-Compustat Merged Data

Our three cash-flow measures require Compustat data, thus restricting our data to a subset of the sample used by Campbell et al. (2001). To ensure that the results obtained from our sample are relevant to the conclusions in Campbell et al., we first examine whether idiosyncratic volatility increases over time in our subsample.

We estimate idiosyncratic volatility for the CRSP-Compustat sample by calculating market-adjusted abnormal returns for each firm month and estimating

[2] Schwert and Seguin (1990) estimate the volatility of monthly returns in a similar fashion. Equation (9) uses the fact that the formula for the absolute value of a normally distributed variable contains a standard deviation term and the fact that the sample-wide mean of $e_{it}$ is equal to zero.



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**Table 2**
**Time trend of idiosyncratic and market-return volatility**

| | Idiosyncratic returns volatility | Market volatility |
|---|---|---|
| Intercept | −121.4 (−9.34) | −26.08 (−1.06) |
| Time | 0.06 (9.05) | 0.01 (0.76) |
| Durbin-Watson | 1.94 | 2.01 |
| Autoregression parameters | | |
| Lag 1 | 0.60 (13.25) | 0.39 (8.57) |
| Lag 2 | 0.16 (3.08) | 0.15 (3.12) |
| Lag 3 | 0.10 (1.93) | 0.04 (0.83) |
| Lag 4 | −0.11 (−2.14) | −0.06 (−1.29) |
| Lag 5 | 0.10 (1.78) | 0.14 (2.78) |
| Lag 6 | 0.03 (0.61) | 0.08 (1.60) |
| Lag 7 | 0.01 (0.10) | −0.02 (−0.36) |
| Lag 8 | −0.00 (−0.03) | 0.05 (1.10) |

Log of mean idiosyncratic variance of returns as a function of time using the CRSP-Compustat sample of firms, 1964–2003. The model is estimated by generalized least squares (Yule-Walker), with *t*-statistics presented in parentheses below the coefficient estimate.

the cross-sectional volatility for each month. Second, we focus on an equal-weighted idiosyncratic risk measure as opposed to the market value-weighted measure used by Campbell et al. (Value weighting reduces the coefficients on idiosyncratic return and cash-flow volatility but does not affect the statistical significance of our results.)

Table 2 presents the time trend of log idiosyncratic volatility in our 1964–2003 CRSP-Compustat subsample. We depart from the previous literature by studying the natural logarithm of volatility. This transformation allows us to interpret the regression slope coefficients on time as growth rates. We correct for the autocorrelation in volatility with a Yule-Walker correction that employs eight monthly lagged autocorrelation parameters; the autocorrelation at lag 1 is the most pronounced, but there is also a significant autocorrelation at lag 2. Durbin-Watson statistics indicate that the Yule-Walker method removes the autocorrelation in these regressions. The 0.06 slope coefficient on time (in years) establishes that idiosyncratic risk has been growing at a 6% average annual rate.

Figure 1 plots the time-series trends for the log of idiosyncratic and market risk in our sample. From Table 2 and Figure 1 we conclude that a significant increase in idiosyncratic volatility is present in the CRSP-Compustat subsample, similar to the CRSP-only sample results reported by Campbell et al.

## 3. Earnings Volatility over Time

Is the increase in return volatility in the CRSP-Compustat sample driven by increasing fundamental volatility—by the volatility in firms' earnings, cash flows, and sales? To answer this question, we estimate fundamental volatility over time by applying the analysis reported in Table 2 to the estimates of fundamental volatility obtained from Equation (9). In calculating fundamental volatility, we winsorize the top and bottom 5% of monthly individual volatilities

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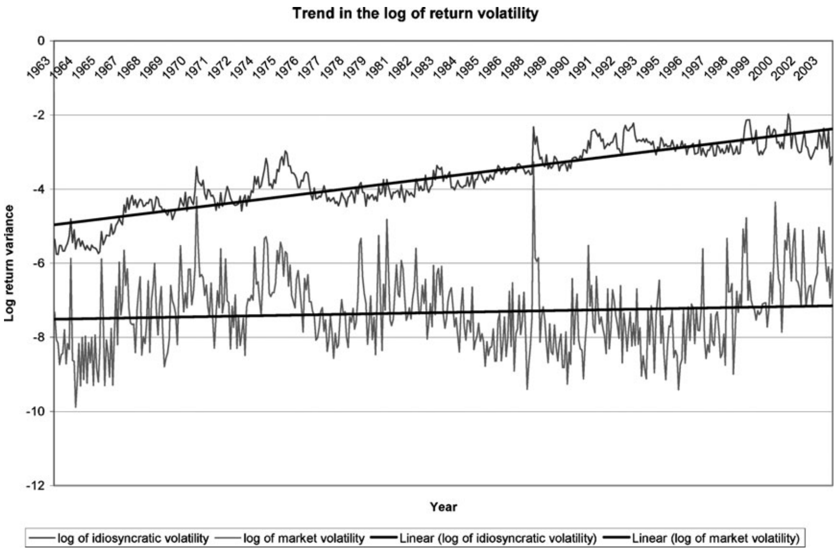


**Figure 1**
**Idiosyncratic return volatility**

**Table 3**
**Time trend of idiosyncratic cash-flow volatility**

| | Earnings per share ($) | Cash-flow per share ($) | Sales per share ($) |
|---|---|---|---|
| Intercept | −324.35 (−8.83) | −307.92 (−8.61) | −111.51 (−2.15) |
| Time | 0.16 (8.64) | 0.15 (8.42) | 0.05 (2.03) |
| Durbin-Watson | 1.96 | 1.96 | 1.97 |
| Autoregression parameters | | | |
| Lag 1 | 1.09 (23.70) | 1.08 (23.34) | 1.09 (23.82) |
| Lag 2 | −0.12 (−1.94) | 0.11 (1.81) | −0.05 (−0.75) |
| Lag 3 | −0.25 (−4.15) | −0.19 (−3.12) | −0.40 (−5.92) |
| Lag 4 | 0.24 (3.97) | 0.18 (2.98) | 0.33 (−4.79) |
| Lag 5 | 0.04 (0.71) | 0.04 (0.59) | −0.06 (−0.84) |
| Lag 6 | −0.50 (−8.39) | −0.48 (−8.01) | −0.16 (−2.36) |
| Lag 7 | 0.50 (7.82) | 0.48 (7.67) | 0.11 (1.64) |
| Lag 8 | 0.05 (1.02) | −0.04 (−0.87) | 0.10 (2.23) |

Log of mean idiosyncratic variance of (i) earnings shock per share; (ii) cash-flow shock per share; and (iii) sales shock per share as a function of time. The model is estimated by generalized least squares (Yule-Walker), with $t$-statistics presented in parentheses below the coefficient estimate.

before computing the monthly mean, to reduce the disproportionate effect of extreme observations.

Table 3 presents the results for earnings per share, cash flow per share, and sales per share. After controlling for serial correlation in the residuals, the model for idiosyncratic volatility indicates a significant increase in volatility for all three cash-flow measures. The coefficient on the time trend in the earnings volatility equation is the largest single coefficient at 0.16 (suggesting 16% annual growth in earnings volatility), but all three coefficients are comparable



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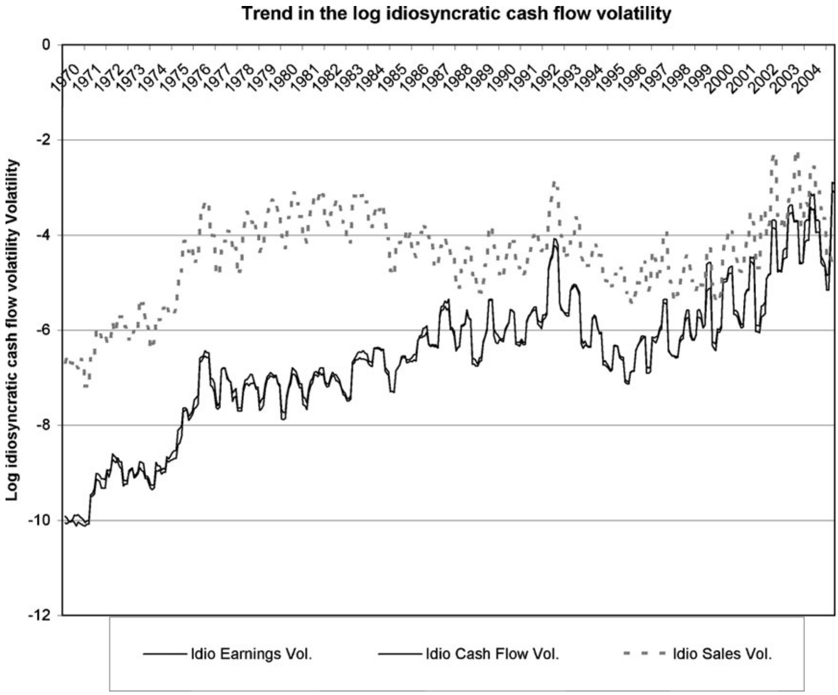


**Figure 2**
**Idiosyncratic fundamental volatility**

to or larger than the coefficient on the time trend (0.06) in the idiosyncratic returns volatility regression in Table 2.

Figure 2 plots the time series of all three measures of fundamental idiosyncratic volatility over the sample period. The scale of the growth in fundamental volatility is large enough to explain the growth in the volatility of idiosyncratic returns. If anything, the market seems to *underreact* relative to the idiosyncratic volatility in cash flows. This finding has important implications for the trading-based behavioral explanations of the increase in idiosyncratic volatility. For example, the activity of retail traders, characterized by the rapid increase of day-trading activity in the 1990s, has been proffered as an explanation for increased return volatility (Brandt, Brav, and Graham, 2005). Along these lines, Chordia, Roll, and Subrahmanyam (2001) suggest that declining transaction costs are responsible for increased volatility and volume.

In contrast to the day-trading argument, several papers suggest that institutions are more strongly associated with increased idiosyncratic volatility than are individual investors. Malkiel and Xu (2003) and Dennis and Strickland (2004) find a positive cross-sectional relation between idiosyncratic volatility and institutional ownership. Malkiel and Xu interpret these results as suggesting that institutional trading causes idiosyncratic risk. Bennett, Sias, and



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Starks (2003) contend that institutional investors' changing preferences for small stocks have contributed to greater idiosyncratic volatility, particularly for small stocks.

Our results suggest that the trend in idiosyncratic fundamental volatility is sufficient to explain the increase in idiosyncratic stock-return volatility. Thus, appeals to trading-based explanations are unnecessary. Since it is unlikely that institutional trading causes higher fundamental volatility, we assert that institutional turnover responds to idiosyncratic volatility—i.e., the causal link between institutional ownership and idiosyncratic volatility runs in the opposite direction to that put forth by Malkiel and Xu (2003) and Dennis and Strickland (2004). Furthermore, in light of Malkiel and Xu's Granger causality test, our results imply that institutional trading anticipates future changes in idiosyncratic volatility. Our explanation is consistent with the paradigm that the role of some financial institutions such as mutual funds is to provide economies of scale for investors seeking diversification. If so, these financial institutions should hold more idiosyncratic firms, since they have a comparative advantage in managing large portfolios.

### 3.1 The influence of firm composition

One explanation for the increase in idiosyncratic risk is that Compustat-CRSP coverage has changed. Perhaps rather than firms becoming more volatile, more volatile firms have entered the sample. Such a finding might coincide with the relaxation of the requirements needed for a firm to list on an exchange (Brown and Kapadia, 2007).

We investigate four versions of this explanation. First, is the increase in volatility attributable to a larger proportion of smaller firms? Second, has there been an increase in the proportion of firms in more volatile industries? Third, irrespective of size and industry, are new listings or new data coverage the source of the increase in volatility? Fourth, to what extent can the increase in volatility be attributable to a trend toward less firm-level diversification?

For the first investigation we separate all firms into a small and large market capitalization sample. Inclusion into these samples depends on whether the firm has market capitalization that is greater or less than the inflation-adjusted median market capitalization for the sample in the fourth quarter of 1963. If listing requirements have enabled smaller firms to list, this methodology would leave the large market capitalization sample unaffected since it is determined by the market capitalization distribution in the beginning of the sample. Panel A of Table 4 shows that the small firm sample has an increase in idiosyncratic cash flows that is similar to that of the full sample, although idiosyncratic sales volatility is now insignificant. Panel B shows that the large firms still have an increase in idiosyncratic volatility that is lower than that of small firms, but the increase in large-firm idiosyncratic volatility is statistically significantly for both earnings and cash flows.



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**Table 4**
**Time trend of idiosyncratic cash-flow volatility within size groups**

| | Earnings per share ($) | Cash-flow per share ($) | Sales per share ($) |
|---|---|---|---|
| Panel A: Small-cap firms | | | |
| Intercept | −306.57 (−9.50) | −291.92 (−9.18) | −87.70 (−1.75) |
| Time | 0.15 (9.30) | 0.14 (8.98) | 0.04 (1.66) |
| Durbin-Watson | 1.92 | 1.93 | 1.97 |
| Autoregression parameters | | | |
| Lag 1 | 1.05 (22.15) | 1.05 (22.23) | 1.13 (23.83) |
| Lag 2 | −0.11 (−1.63) | 0.11 (1.76) | −0.12 (−1.69) |
| Lag 3 | −0.20 (−3.32) | −0.17 (−2.75) | −0.30 (−4.32) |
| Lag 4 | 0.20 (3.31) | 0.16 (2.63) | 0.28 (−3.97) |
| Lag 5 | 0.03 (0.48) | 0.06 (1.00) | −0.09 (−1.23) |
| Lag 6 | −0.48 (−7.83) | −0.48 (−7.79) | −0.20 (−2.90) |
| Lag 7 | 0.46 (7.17) | 0.44 (6.80) | 0.22 (3.08) |
| Lag 8 | 0.02 (0.41) | −0.01 (−0.24) | 0.05 (1.16) |
| Panel B: Large-cap firms | | | |
| Intercept | −117.29 (−3.76) | −106.93 (−3.21) | −146.86 (−1.02) |
| Time | 0.05 (3.46) | 0.05 (2.93) | 0.02 (0.87) |
| Durbin-Watson | 1.99 | 2.00 | 1.98 |
| Autoregression parameters | | | |
| Lag 1 | 0.98 (21.09) | 0.99 (21.39) | 1.04 (22.65) |
| Lag 2 | −0.01 (−0.23) | −0.03 (−0.48) | −0.02 (−0.33) |
| Lag 3 | −0.30 (−5.07) | −0.26 (−4.40) | −0.50 (−7.63) |
| Lag 4 | 0.38 (6.27) | 0.34 (5.57) | 0.47 (6.85) |
| Lag 5 | −0.12 (−1.98) | −0.10 (−1.63) | −0.07 (−0.96) |
| Lag 6 | −0.35 (−5.89) | −0.38 (−6.45) | −0.24 (−3.72) |
| Lag 7 | −0.40 (−6.44) | 0.42 (6.79) | 0.23 (3.45) |
| Lag 8 | −0.01 (−0.30) | −0.01 (−0.23) | 0.05 (0.98) |

Log of mean idiosyncratic variance of (i) earnings shock per share; (ii) cash-flow shock per share; and (iii) sales shock per share as a function of time. Idiosyncratic volatility is computed relative to an equally weighted index but aggregated based on initial (1964) industry market capitalization weights for all sample months. The model is estimated by generalized least squares (Yule-Walker), with *t*-statistics presented in parentheses below the coefficient estimate.

We also consider industry composition. We calculate the proportion of firms in each of 49 industries (based on the Fama-French, 1997 classification) as of the fourth quarter of 1963. Instead of using equal weights, each firm's weight is based on its 1964 industry weight. For example, if a growing industry has an increase in individual firm members that is 100% greater than the average industry, each firm is weighted by half. The results of this experiment are contained in Table 5. The constant industry-weighted cash-flow volatilities all exhibit comparable trends to the equal-weighted results in Table 3. Again, all three trends are statistically significant. Thus, the increase in idiosyncratic risk has affected both growing and contracting industries.

Perhaps, irrespective of differences in industry composition and size, more volatile firms have been listed on exchanges. We investigate this by restricting our sample to the older firms that existed in the first 10 years (1964–1973) of our sample. This experiment controls for changes in listing requirements as well as changes in data coverage.[3] As is shown in Table 6, this produces positive

[3] Unlike Brown and Kapadia (2007), this test is not influenced by data inclusion. From Brown and Kapadia's sample collection description and their self-reported number of sample firms, we found that Compustat exclusion results



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**Table 5**
**Time trend of idiosyncratic cash-flow volatility holding industry distribution constant**

| | Earnings per share ($) | Cash-flow per share ($) | Sales per share ($) |
|---|---|---|---|
| Intercept | −338.03 (−9.40) | −311.94 (−8.83) | −111.78 (−2.52) |
| Time | 0.17 (9.20) | 0.15 (8.63) | 0.05 (2.42) |
| Durbin-Watson | 1.92 | 1.96 | 1.95 |
| Autoregression parameters | | | |
| Lag 1 | 1.02 (22.84) | 1.05 (22.84) | 0.99 (21.52) |
| Lag 2 | −0.07 (−1.17) | −0.10 (−1.53) | 0.04 (0.57) |
| Lag 3 | −0.20 (−3.42) | −0.18 (−3.04) | −0.31 (−4.94) |
| Lag 4 | 0.18 (3.00) | 0.18 (2.98) | 0.25 (−3.81) |
| Lag 5 | 0.07 (1.20) | 0.04 (0.72) | −0.07 (−1.15) |
| Lag 6 | −0.48 (−8.16) | −0.49 (−8.41) | −0.18 (−2.90) |
| Lag 7 | 0.45 (7.11) | 0.50 (8.01) | 0.17 (−2.63) |
| Lag 8 | −0.01 (−0.23) | −0.05 (−1.06) | 0.10 (2.13) |

Log of mean idiosyncratic variance of (i) earnings shock per share; (ii) cash-flow shock per share; and (iii) sales shock per share as a function of time. Idiosyncratic volatility is computed relative to an equally weighted index but aggregated based on initial (1964) industry market capitalization weights for all sample months. The model is estimated by generalized least squares (Yule-Walker), with *t*-statistics presented in parentheses below the coefficient estimate.

**Table 6**
**Time trend of idiosyncratic cash-flow volatility for early sample firms**

| | Earnings per share ($) | Cash-flow per share ($) | Sales per share ($) |
|---|---|---|---|
| Intercept | −225.55 (−5.23) | −215.07 (−5.00) | −115.38 (−2.13) |
| Time | 0.11 (5.06) | 0.10 (4.82) | 0.05 (2.04) |
| Durbin-Watson | 1.97 | 1.98 | 1.99 |
| Autoregression parameters | | | |
| Lag 1 | 1.05 (22.77) | 1.02 (22.13) | 1.07 (23.32) |
| Lag 2 | −0.08 (−1.15) | −0.04 (−0.56) | −0.05 (−0.71) |
| Lag 3 | −0.36 (−5.52) | −0.29 (−4.57) | −0.49 (−7.33) |
| Lag 4 | 0.38 (5.65) | 0.28 (4.32) | 0.45 (6.29) |
| Lag 5 | −0.04 (−0.67) | −0.04 (−0.61) | −0.05 (−0.84) |
| Lag 6 | −0.26 (−4.03) | −0.27 (−4.28) | −0.10 (−1.55) |
| Lag 7 | 0.29 (4.37) | 0.29 (4.47) | 0.05 (0.75) |
| Lag 8 | −0.03 (−0.64) | −0.00 (−0.02) | 0.10 (2.15) |

Log of mean idiosyncratic variance of (i) earnings shock per share; (ii) cash-flow shock per share; (iii) sales shock per share; and (iv) returns as a function of time. The sample consists of all firms that were included in the first 10 years of our sample period (1964–1973), estimated over the 1964–2003 period. The model is estimated by generalized least squares (Yule-Walker), with *t*-statistics presented in parentheses below the coefficient estimate.

and statistically significant time trends for all three measures. The time trend in idiosyncratic cash-flow and earnings volatility is about 1/3 smaller than the full sample estimates in Table 3. The time trend in idiosyncratic sales volatility is unchanged.

Last, the tendency to break up conglomerate firms into smaller, more focused firms could explain the increase in idiosyncratic volatility (Campbell et al., 2001). Idiosyncratic cash-flow shocks to one division of a diversified conglomerate are likely to be offset by idiosyncratic cash-flow shocks to another division. Because the proportion of diversified firms in the economy decreased with the conglomerate breakups of the 1980s, such dampening of

in a dramatic loss of observations. For example, including firms with no Compustat data increases their 1997 sample by 39.1%.



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typical firm volatility should have become less prevalent, resulting in higher average idiosyncratic volatility.

We test whether the breakup of diversified firms explains our results by examining the change in fundamental volatility over time for firms with and without multiple lines of business. Lines of business can be obtained from the Compustat Industrial Segment database. We obtain the number of business segments for the period 1980–2002.[4] Unfortunately, the data are disrupted by Financial Accounting Standards Board Statement (FASB) No. 131, issued in 1997, on the reporting of segment information. FASB 131 changed the focus of segment reporting from industries to internal reporting lines. As a result, the reported number of business segments increased and the reported number of single-segment firms initially decreased precipitously (Berger and Hann, 2003). Because of this structural break, the segment data are unreliable after 1997, and we thus analyze only the 1980–1997 time series of business information.

Table 7 examines idiosyncratic cash-flow volatility over the 1980–1997 period for single-segment and multisegment firms separately. We find that idiosyncratic volatility increased significantly for both single-segment and multisegment firms. Over this subperiod, the coefficients on the time trend of earnings and cash flow are significant, and comparable for both types of firms, though the sales coefficient is insignificant. These findings are consistent with Roll (1988), who constructs portfolios of smaller firms to match NYSE and AMEX firms in aggregate size; Roll's portfolios exhibit much larger $R^2$s than their corresponding size-matched firms, indicating that diversification fails to explain larger firms' higher observed $R^2$s.

## 3.2 Time-series properties

Table 3 reports that all three cash-flow series have large and persistent autocorrelation coefficients, suggesting that the series might be integrated and, therefore, our conclusions could be based on inappropriate test statistics. Table 8 investigates whether our conclusions are appropriate given the time-series properties of idiosyncratic cash flows and returns.

Table 8 presents three different time-series tests. The unit root tests are Dickey-Fuller test statistics for each series. The "no trend" results model each series as following a first-order autoregressive process with no trend, whereas the "trend" results incorporate a time trend in the autoregressive process. Since we expect a trend in our series, we expect the "no trend" results to provide the strongest support for a unit root. This is in fact the case that two separate tests on the first-order autoregressive series fail to reject the hypothesis of a unit root for idiosyncratic earnings and cash flows, although the tests reject the null for idiosyncratic sales volatility. Alternatively, when the time-series specification contains a trend, the hypothesis that the series contains a unit root is strongly

[4] Business segment data begin in 1978, although Compustat reports a rolling 19-year window, dropping older years as new years are added, so currently the oldest reported year is 1985. With the help of other researchers we were able to recover data going back to 1980.



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**Table 7**
**Focus, diversification, and idiosyncratic cash-flow volatility**

| | Earnings per share ($) | Cash flow per share ($) | Sales per share ($) |
|---|---|---|---|
| | Panel A: Single-segment firms | | |
| Intercept | −163.15 (−2.55) | −127.18 (−2.21) | 80.11 (1.25) |
| Time | 0.08 (2.47) | 0.06 (2.13) | −0.04 (−1.29) |
| Durbin-Watson | 1.97 | 1.99 | 1.96 |
| Autoregression parameters | | | |
| Lag 1 | 0.98 (14.11) | 1.02 (14.77) | 1.12 (16.02) |
| Lag 2 | 0.04 (0.45) | −0.01 (−0.15) | −0.10 (−0.99) |
| Lag 3 | −0.24 (−2.86) | −0.27 (−3.20) | −0.41 (−4.05) |
| Lag 4 | 0.22 (2.50) | 0.26 (3.01) | 0.42 (4.05) |
| Lag 5 | −0.08 (−0.93) | −0.07 (−0.79) | −0.04 (−0.34) |
| Lag 6 | −0.46 (−5.23) | −0.51 (−5.93) | −0.31 (−3.06) |
| Lag 7 | 0.46 (4.93) | 0.52 (5.58) | 0.26 (2.55) |
| Lag 8 | −0.00 (−0.03) | −0.03 (−0.49) | −0.03 (−0.44) |
| | Panel B: Multisegment firms | | |
| Intercept | −191.45 (−3.00) | −175.17 (−2.92) | 29.94 (0.51) |
| Time | 0.09 (2.92) | 0.08 (2.84) | −0.02 (−0.57) |
| Durbin-Watson | 1.97 | 1.97 | 1.98 |
| Autoregression parameters | | | |
| Lag 1 | 0.96 (13.73) | 1.06 (15.28) | 0.99 (14.18) |
| Lag 2 | 0.10 (1.02) | −0.06 (−0.55) | 0.05 (0.49) |
| Lag 3 | −0.33 (−3.62) | −0.29 (−2.89) | −0.36 (−3.74) |
| Lag 4 | 0.25 (2.68) | 0.23 (2.25) | 0.22 (2.19) |
| Lag 5 | −0.04 (−0.40) | 0.02 (0.18) | 0.03 (0.37) |
| Lag 6 | −0.33 (−3.61) | −0.16 (−1.62) | −0.11 (−1.15) |
| Lag 7 | 0.27 (2.91) | 0.09 (0.90) | 0.05 (0.55) |
| Lag 8 | 0.04 (0.45) | 0.03 (0.42) | 0.01 (0.17) |

Log mean idiosyncratic cash-flow volatility as a function of time using the merged CRSP-Compustat and Compustat segment sample of firms, 1980–1997. Single-segment (multisegment) firms are identified as having a single (more than one) business segment in each calendar year on the Compustat segment database: 73.0% (27%) of firm observations are classified as single-segment (multisegment). The model is estimated by generalized least squares (Yule-Walker) with $t$-statistics presented in parentheses below the coefficient estimate.

**Table 8**
**Time-series properties of idiosyncratic volatility**

| | Returns | Earnings | Cash flows | Sales |
|---|---|---|---|---|
| *Unit root tests* | | | | |
| No trend-–$\rho$ | −19.91 (0.01) | −5.96 (0.35) | −5.27 (0.40) | −12.94 (0.06) |
| No trend-–$\tau$ | −3.34 (0.04) | −1.74 (0.41) | −1.59 (0.49) | −2.58 (0.10) |
| Trend—$\rho$ | −70.53 (0.00) | −34.81 (0.00) | −31.26 (0.01) | −19.88 (0.07) |
| Trend—$\tau$ | −5.92 (0.00) | −4.24 (0.01) | −3.98 (0.01) | −3.13 (0.10) |
| $PSW^1$ test | 13.09 (0.01) | 4.38 (0.01) | 4.09 (0.01) | 0.43 (>0.10) |
| *Regression tests* | | | | |
| Residual trend | n/a | 0.00 (0.68) | 0.00 (0.67) | 0.04 (0.01) |

Returns, earnings, cash flows, and sales are monthly idiosyncratic volatility series from 1964 to 2003. Unit root tests are Dickey-Fuller tests for the presence of a unit root in each series. The $PSW^1$ test is one of a series of trend tests developed by Vogelsang (1989) that are valid under I(0) or I(1) processes. The specific tests reported use asymptotic $p$-values reported in Vogelsang's Table II. The regression tests assume an I(0) process for idiosyncratic volatility. These tests present Yule-Walker coefficients and $p$-values for coefficients in two tests of the idiosyncratic returns volatility residuals. The *Residual trend* is a test for the trend in the residuals of idiosyncratic return volatility regressed on idiosyncratic earnings, cash flows, and sales volatility, respectively. $p$-values for all tests are presented in parentheses next to the appropriate test statistic.

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rejected for returns, earnings, and cash-flow volatility, and less strongly rejected for sales volatility.

Although the unit root tests suggest that these series are stationary, we also conduct a test designed by Vogelsang (1989), who derives a unit root test that is robust to whether the underlying process is stationary or nonstationary. Vogelsang's $PSW^1$ test statistic confirms the presence of a time trend in returns, earnings, and cash flows at the 1% level, but sales show more persistence and the test fails to reject at conventional significance levels. Given the results of these tests, modeling returns, earnings, and cash flows as stationary is the correct description of their time-series processes.[5]

The trend stationarity of the idiosyncratic volatility time series allows us to first estimate standard regressions of idiosyncratic return volatility on idiosyncratic fundamental volatility and an intercept. We then regress the residuals from this first regression on a time trend. The *Residual trend* row of Table 8 presents the time-trend slope coefficient and the associated $p$-values for this coefficient. Both earnings and cash-flow volatility effectively remove the trend in idiosyncratic return volatility, as neither of the coefficients is significant at the 5% level. This finding is consistent with the hypothesis that idiosyncratic return and cash-flow volatility share a common trend. Controlling for earnings or cash-flow volatility effectively removes the trend in idiosyncratic returns volatility. There appears to be a short-term trend between these series; unreported regressions demonstrate that idiosyncratic return volatility significantly forecasts earnings, cash-flow, and sales idiosyncratic volatility for the following two quarters.

## 4. Competition

In this section, we examine whether increased competition in the economy can explain increases in idiosyncratic risk over time. Although not all forms of competition increase idiosyncratic volatility, some forms of competition could do so, such as the type of competition that is attributable to consumers demonstrating less loyalty to a given firm's product. A reduction in consumer loyalty could occur when search costs between firms are lower, when it is easier for customers to compare products, or when branding is a less important feature for the product. Our model is similar to Raith (2003), who models market power as a function of product transportation costs. Raith's model generates the implication that competition causes more firm-level profit volatility. Other models take a different approach but generate the same implication. For example, Philippon (2003) develops a model that shows how price rigidities lead to a linkage between competition and idiosyncratic risk. We envision a type of competition

[5] Untabulated cointegration tests examine the nature of the relation between idiosyncratic return volatility and our three idiosyncratic cash-flow volatility series. Using the method of Phillips and Ouliaris (1990), we can reject the null of a unit root in the residual series, in favor of a cointegrating vector. This result is not surprising since our earlier tests lend support to the stationarity of these series.



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in which consumers shift their demand between firms within an industry, as opposed to changing their total demand for the industry's product.[6] When a particular consumer ceases to purchase the product from one firm and initiates a relationship with a second firm, the first firm loses product to the benefit of the second firm, inducing a lower correlation between the firms' cash flows, and therefore, more idiosyncratic risk. Some examples of this type of competition include charge card solicitations that entice a consumer to transfer balances from a competitor, long-distance carrier promotions that pay customers to leave a competitor, and search engines that enable Internet consumers to compare prices from several vendors.

## 4.1 Analytical example

The impact of easier substitution between products can be illustrated with an example. Consider a two-firm industry in which the firms have the following cost functions:

$$C_1 = \frac{w_1}{2} q_1^2 \tag{10}$$

and

$$C_2 = \frac{w_2}{2} q_2^2. \tag{11}$$

The parameters $w_1$ and $w_2$ can be considered as either input costs or a technological parameter that affects productivity. We assume that the $w$'s are stochastic and thus a source of volatility shocks to the production process. The prices of the two firms' products are denoted by

$$p_1 = \theta - q_1 - kq_2 \tag{12}$$

and

$$p_2 = \theta - q_2 - kq_1, \tag{13}$$

where $\theta$ is an industry demand shock that is common to both firms, and $k$ is a parameter assumed to lie between zero and unity that is related to how closely consumers view the two products as substitutes. When $k = 0$, no substitution occurs and both firms produce as monopolists. For positive $k$, each firm's production decision is determined by a Cournot equilibrium, in which each firm solves for optimal production treating the other firm's production decision as given. For the case of $k = 1$, the standard case of Cournot competition maintains.

[6] One example is provided by Agarwal, Baranth, and Viswanathan (2004), who document a link between eCommerce adoption and volatility, which they attribute to increased demand uncertainty as well as product market competition following eCommerce adoption.

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We assume that both firms observe the shocks to $\theta$, $w_1$, and $w_2$ at the beginning of each period, and choose optimal production within the time period based on this knowledge.

We can write firm 1's profit function as

$$\pi_1 = (\theta - q_1 - kq_2)\, q_1 - \frac{w_1}{2} q_1^2. \tag{14}$$

The first-order condition to maximize profit can be written as

$$0 = \theta - kq_2 - q_1\,(2 + w_1)\,. \tag{15}$$

Solving for $q_1$,

$$q_1 = \frac{\theta - kq_2}{2 + w_1}. \tag{16}$$

Appealing to the definition of Cournot equilibrium and to the fact that the firms are isomorphic, the optimal quantities are given by

$$q_1 = \frac{\theta\,(2 + w_2 - k)}{(2 + w_1)\,(2 + w_2) - k} \tag{17}$$

and

$$q_2 = \frac{\theta\,(2 + w_1 - k)}{(2 + w_1)\,(2 + w_2) - k}. \tag{18}$$

Substituting (17) and (18) into (14) yields the optimal profit for firm 1,

$$\pi_1 = \frac{\theta^2\,(2 + w_2 - k)\,(2k^2 + (2 + w_1)\,(2 + w_2) - k\,(4 + w_1))}{2\,(k - (2 + w_1)\,(2 + w_2))^2}.$$

The analogous formula can be solved for firm 2's profit. From these equations we investigate the impact of shocks to $\theta$, $w_1$, and $w_2$ on the correlation between the firms' profits. Specifically, we assume that $\theta$ can be 0.8, 1.0, or 1.2, each with probability 1/3, and $w_1$ and $w_2$ can be 0.5, 1.0, or 1.5, again each with probability 1/3. We assume that all three shocks are independent. This framework creates 27 ($3 \times 3 \times 3$) distinct states, each with equal probability. For each individual state we compute both firms' profits. Using the production and profit outcome from all possible states, we compute the correlation between profits.

Figure 3 graphs the relation between the competition parameter $k$ and the correlation between the two firms' profits and sales. The source of positive correlation between firms comes from the industry-wide shocks $\theta$, whereas the negative correlation is induced from the input price shocks $w_1$ and $w_2$. As the industry becomes more competitive ($k$ increases), both correlations fall.



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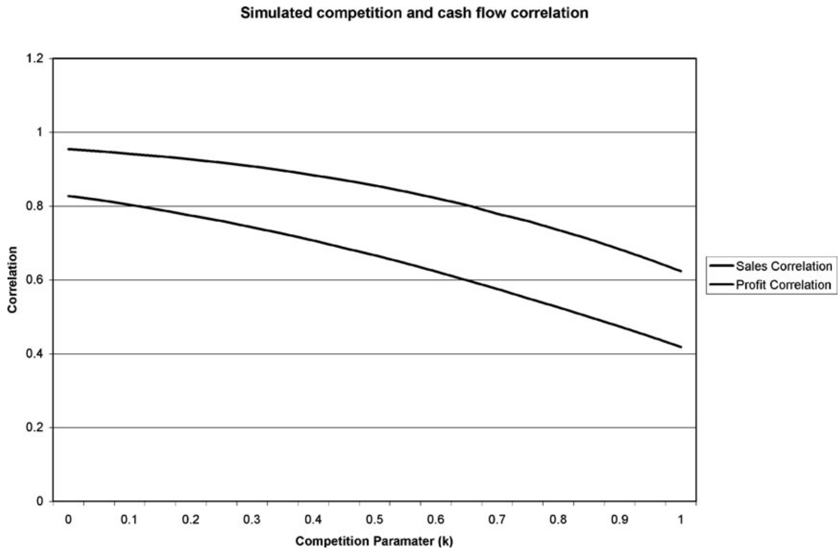


**Figure 3**
**Competition and cash-flow correlation**

## 4.2 The empirical time trend of competitiveness

We analyze the validity of our competitiveness explanation by first examining three variables that we expect are proxies for competition: industry turnover, return on assets, and the market share of foreign competitors. As demonstrated by Chamberlin (1933) and Robinson (1933), enduring monopoly power requires barriers to entry. Monopoly profit also implies that monopolists are unlikely to exit their industries. We expect that exit and entry from an industry will proxy for the market power of the firms within the industry. Using CRSP data we construct a turnover index by computing the market value of new entries plus the market value of exits divided by total industry market value. Because our turnover index uses CRSP listing codes, we ignore new lists that are associated with CRSP increasing its exchange coverage, such as new NASDAQ listings in January 1973. Because we classify industry turnover, each firm in the industry is assigned a monthly industry turnover measure that is the same as that of the other firms in the industry.

Our second proxy for market power is return on assets. Firms with market power will generate higher profits, on average, than firms that do not have market power. We compute this variable by summing a firm's earnings (Computstat data item 8) and interest payments (22) over the past four quarters and dividing the result by last quarter's assets (44).

Our third proxy for competition is the domestic industry market share of foreign competitors. This proxy is computed from the updated NBER-CES Manufacturing Industry database, as documented by Feenstra (1996). This



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**Table 9**
**Cross-sectional and time-series influence of return on assets on idiosyncratic stock-returns volatility**

| Independent variable | Specification | | | |
|---|---|---|---|---|
| Intercept | −4.73 (−147.32) | −4.79 (−153.92) | −4.25 (−19.93) | −4.20 (−28.55) |
| ROA | −1.73 (−47.33) | −1.75 (−48.80) | | −1.70 (−47.32) |
| Missing ROA dummy | 0.14 (10.71) | 0.15 (10.95) | | 0.14 (10.72) |
| Industry turnover | 0.26 (4.53) | 0.12 (2.13) | 0.32 (5.18) | |
| Foreign market share | 0.31 (8.13) | | 0.29 (7.02) | 0.31 (8.15) |
| Missing foreign market share dummy | −0.16 (−7.86) | | −0.21 (−9.64) | −0.16 (−7.83) |
| Monthly fixed effects | Yes | Yes | Yes | Yes |
| $R^2$% | 16.89 | 16.08 | 12.28 | 16.89 |

Estimation of the effect of firm level idiosyncratic volatility on (1) the reported four-quarter return on assets from quarterly statements that ended at least 3 months in the past; (2) a dummy variable that equals 1 if return on assets is missing; and (3) the 2-month prior turnover of the firm's industry. Standard errors control for both time-series and cross-sectional variation using firm-clustered standard errors and monthly dummy variables as in Petersen (2005). *t-statistics* are presented in parentheses. The sample covers 1972 through 2001.

database provides annual data from 1964 to 2001 on SIC-level production, imports, and exports. Production data for 1995–2001 are from the corresponding US Census Bureau's Annual Survey of Manufactures. Using the Fama-French (1997) industry classifications, we aggregate these data at the industry level. Our proxy for industry market share from foreign competitors (ICOMP) is computed as (imports)/(shipments – exports).

To ensure that our accounting information is public before idiosyncratic volatility is realized, we measure our industry turnover measure 2 months before our idiosyncratic risk measure, and our ROA measure uses accounting data that are available three or more months after the end of the quarter. Also, we limit our ROA estimation to the post-1972 portion of our data, since the Compustat data required to compute return on assets are not widely available before 1972. In order to include firms with missing Compustat data, we assign ROA a value of 0 if the required Compustat data are missing and we assign a missing ROA dummy variable a value of 1. Firms with ROA data are assigned a missing ROA dummy equal to 0. This procedure allows us to utilize all the data, while producing the same slope coefficient on ROA that is attained if firms with missing ROA are discarded. Since the NBER-CES data lack coverage of some industries, we use a similar adjustment for the industry market share from foreign competitors (ICOMP)—we assign missing ICOMP values a value of 0 if the data are missing, and correspondingly create a dummy variable that is equal to 1 when the underlying ICOMP data are missing and 0 otherwise.

Table 9 estimates the cross-sectional relation between idiosyncratic return risk and industry turnover, return on assets, and market share from foreign competitors. Following Petersen (2005), we estimate the regression with firm-clustered standard errors and time-based fixed effects. We obtain similar results when we estimate the regressions using the Fama-MacBeth (1973) procedure with standard errors adjusted for eighth-order time-series dependence following Pontiff (1996). The results in Table 9 support the notion that these proxies

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for market power relate to idiosyncratic volatility. There is a strong negative relation between ROA and future idiosyncratic volatility and there is a strong positive relation between industry turnover and future idiosyncratic volatility. As predicted, there is a statistically significant positive relation between market share from foreign competitors and idiosyncratic return volatility. Our proxies for competition have a strong cross-sectional effect on idiosyncratic volatility.

A time-series analysis is needed to ascertain whether our competition proxies suggest a trend toward more competition. Unlike in the cross-sectional tests, we do not use a missing variable transformation, and thus our ROA and ICOMP variables sometimes have missing data. Each data point represents an average across all firms with data. Since ICOMP and turnover are calculated at the industry level, industries with larger numbers of firms will have a larger influence on the time-series plot. Figure 4 examines the time-series properties of the cross-sectional averages of all three of our proxies. As the top plot demonstrates, there has been a trend toward lower ROA. In fact, since the late 1980s, the average ROA has tended to be negative, consistent with a trend toward more aggressive competition. The second plot is consistent with increases in industry turnover, especially in the 1999–2002 period. The last plot demonstrates a notable increase in foreign competition. Over this time period, the typical domestic industry experienced a sevenfold increase in foreign market share. This plot is marked by substantial annual variation and minor monthly variation since information on industry sales and import data is generated annually, yet the monthly averages vary as the number of firms shifts within the year.

### 4.3 Evidence from deregulated industries

Several industry groups have experienced significant deregulation over the past 40 years. Since deregulation reduces the barriers to entry that enable market power, we test for the impact of deregulation on idiosyncratic risk by examining whether deregulated industries experience higher or lower than normal increases in idiosyncratic volatility. We use the seven industries that Andrade, Mitchell, and Stafford (2001) list as having undergone a discrete deregulatory experience: airlines (deregulated in 1978), banks and thrifts (1994), entertainment (1984), natural gas (1978), telecommunications (1996), trucking (1980), and utilities (1992).

We form industries using an extension of the Fama-French (1997) 49 industry group classifications, in which we create new subindustries that correspond to the Andrade, Mitchell, and Stafford (2001) deregulated industries. Specifically, we form an airline industry (AIR) from firms with SIC codes between 4500 and 4599 that were previously included in the transportation industry (TRANS); an entertainment industry (ENTR) from firms with SIC codes between 7800 and 7841 that were previously included in the broader Fama-French entertainment industry (FUN); a natural gas industry (NTGAS) from firms with SIC codes between 1310 and 1389 that were previously included in petroleum and natural gas (ENRGY); a trucking industry from firms with SIC codes between 4210 and

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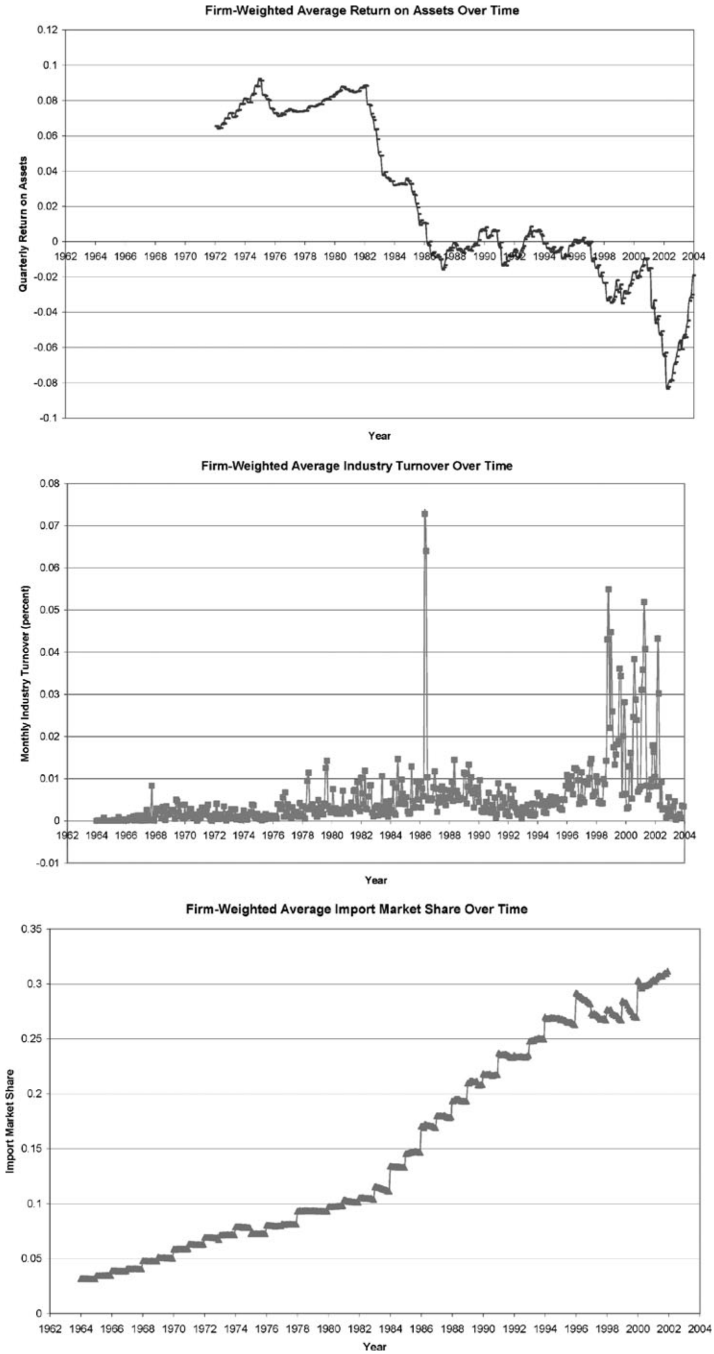


**Figure 4**
**Time-series plots of proxies for market power 1962–2003**



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**Table 10**
**Idiosyncratic volatility and deregulation**

| | Before deregulation | | After deregulation | | Difference |
|---|---|---|---|---|---|
| | *N* | Mean | *N* | Mean | |
| Panel A: Log-relative idiosyncratic volatility of deregulated industries, where idiosyncratic risk is defined relative to an equal-weighted market index | | | | | |
| Air transport | 156 | 0.001 | 324 | −0.1338 | −0.135 |
| Banks and thrifts | 228 | −1.182 | 252 | −0.910 | 0.272 |
| Entertainment | 228 | 0.429 | 252 | 0.561 | 0.132 |
| Natural gas | 156 | 0.304 | 324 | 0.275 | −0.029 |
| Telecommunications | 372 | −0.275 | 108 | 0.115 | 0.390 |
| Trucking | 180 | −0.344 | 300 | −0.161 | 0.181 |
| Utilities | 324 | −1.292 | 156 | −0.868 | 0.425 |
| Average difference *t*-test | | | | | 0.177 (2.26) |
| Panel B: Log-relative idiosyncratic volatility of deregulated industries, where idiosyncratic risk is defined relative to an equal-weighted industry index | | | | | |
| Air transport | 156 | −0.108 | 324 | −0.161 | −0.0532 |
| Banks and thrifts | 228 | −1.266 | 252 | −0.918 | 0.349 |
| Entertainment | 228 | 0.404 | 252 | 0.551 | 0.148 |
| Natural gas | 156 | 0.309 | 324 | 0.266 | −0.04 |
| Telecommunications | 372 | −0.276 | 108 | 0.119 | 0.395 |
| Trucking | 180 | −0.394 | 300 | −0.183 | 0.211 |
| Utilities | 324 | −1.328 | 156 | −0.880 | 0.448 |
| Average difference *t*-test | | | | | 0.208 (2.71) |

This table presents data on the magnitude of the log ratio of mean idiosyncratic volatility in deregulated industries divided by the magnitude of mean idiosyncratic volatility in the market. There are a total of 480 industry months in the sample from 1964 to 2003. The *t*-test presents a test of whether relative idiosyncratic volatility in the deregulated industry increases subsequent to the passage of the deregulation legislation.

4219 that were previously included in transportation (TRANS); and a banking and thrift industry (B&THR) for firms with SIC codes between 6000 and 6036 that were previously a subset of the Fama-French banking industry (BANKS). This produces a total of 53 industries.

We consider idiosyncratic risk measures relative to both the market and the particular industry. As described in Section 1, market (industry) idiosyncratic risk is calculated for each firm by computing the variance of the firm's stock return less the return of the equal-weighted market (industry) index in a given month. In order to control for marketwide trends in idiosyncratic risk, we divide this measure by the average idiosyncratic risk of all firms in that month. This ratio is transformed by the natural log operator and an industry average log ratio is computed using all the firms in the industry.

Table 10 presents results using the log relative market (panel A) and log relative industry (panel B) idiosyncratic risk measures. The results in both panels are similar—five of seven industries experience increases in idiosyncratic risk after deregulation. Since our risk variable is measured in logs, we can interpret the difference as a percentage change in risk. The mean change for the log relative market (industry) idiosyncratic risk is 17.7% (20.8%) after deregulation, statistically significant at the 5% (1%) level. These results are consistent with decreases in market power coinciding with increases in idiosyncratic risk.



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## 4.4 Evidence from international competition

The previous section argues that more competitive industries (deregulated industries) have higher idiosyncratic volatility. This section examines whether our cross-sectional conclusion on competitiveness and idiosyncratic volatility can be expanded across countries: do countries whose market environments are more competitive have higher idiosyncratic volatility?

We obtain data on idiosyncratic volatility trends for the G-7 countries from Guo and Savickas (2004). Competitiveness data come from the World Economic Forum. Each year the World Economic Forum produces the Global Competitiveness Index (GCI), which is a rank of country competitiveness. The GCI has an advantage relative to a single-industry deregulation event in that it is extremely broad; it incorporates a great number of factors that can affect the competitive environment in a particular country (Blanke, Paua, and Sala-I-Martin, 2004). The index is disaggregated into three components: technology (50%), public institutions (25%), and macroeconomic environment (25%).

The Guo and Savickas data begin in 1962 for the United States, 1965 for the United Kingdom, and 1973 for all other G-7 countries, and end in 2003. From World Economic Forum published documents we obtain overall country competitiveness ranks for 2003. Our competitiveness explanation implies that both positive changes in competitiveness and positive changes in technology will be associated with positive changes in idiosyncratic risk. A direct test of economy-wide competitiveness changes is not possible as the GCI index did not exist for much of the Guo and Savickas sample period. Rather, we use the 2003 GCI rank as a proxy for the change in economy-wide competitiveness over time. This substitution induces an errors-in-variables problem, which will bias our test statistic toward the null. However, we can directly test our explanation by obtaining data on the change in rank (1973–2003) of a key component of the GCI technology subindex: US patents per capita. While patents per capita represent only part of the GCI, the data are available back to 1973, the first year all G-7 countries had returns data. Thus, the patent data can be used to determine whether changes over time in technological competitiveness are correlated with changes over time in idiosyncratic volatility.

The CI ranks the most competitive environment as 1, and all other countries that are less competitive have higher ranks. Table 11 presents the trend in idiosyncratic volatility for G-7 countries in column 2 and the rank of volatility growth for each country in column 3. Column 4 presents the 2003 overall country competitiveness rank. Column 5 presents the 2003 patents per capita (technological competitiveness) rank, and column 6 presents the change in technological competitiveness from 1973 to 2003.

Spearman's rank correlations between idiosyncratic volatility and competitiveness are presented at the bottom of columns 4, 5, and 6. The large positive correlations between volatility growth and both the 2003 competitiveness rank and the technology rank indicate that more competitive economies have experienced greater increases in idiosyncratic risk.



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**Table 11**
**Country competitiveness and idiosyncratic return volatility**

| | Idiosyncratic volatility | Idiosyncratic volatility | GCI competitiveness | Technological competitiveness | |
|---|---|---|---|---|---|
| Country | Trend | Rank | 2003 rank | 2003 rank | Rank change 1973–2003 |
| Canada | 0.018 | 1 | 16 | 8 | −2 |
| France | 0.008 | 5 | 24 | 11 | −7 |
| Germany | 0.015 | 2 | 13 | 5 | −2 |
| Italy | 0.003 | 7 | 41 | 25 | −8 |
| Japan | 0.012 | 3 | 11 | 2 | 7 |
| UK | 0.007 | 6 | 15 | 17 | −12 |
| USA | 0.012 | 3 | 1 | 1 | 0 |
| Correlation | | | 0.66 | 0.82 | −0.68 |
| *t*-statistic | | | 1.96 | 3.16 | −2.06 |

This table presents rank correlations between country-specific idiosyncratic volatility trends and measures of relative competitiveness. Idiosyncratic volatility trends for the G-7 countries are the value-weighted trends from Guo and Savickas (2004). GCI competitiveness rank is the rank of a country in the World Economic Forum's Global Competitiveness Index in 2003. Technological competitiveness is the US utility patents per capital component of the technology subindex of GCI. Rank change is the change in country rank of the patents per capital component of GCI from 1973 to 2003. Correlation is the Spearman rank correlation between the idiosyncratic volatility trend rank and the competitiveness rank. *t-statistics* for correlations are calculated as in Morrison (1976, p. 103).

Column 6 examines the change in technological competitiveness over time. The more effective a country has been at producing new technology patents, the stronger is the trend in idiosyncratic volatility. These results are all statistically significant, which is surprising given the small sample size. Internationally, relative competitiveness is strongly correlated with idiosyncratic volatility. The results in Table 11 are similar when we use the idiosyncratic volatility trend coefficient in column 2 rather than the relative rank.

### 4.5 Other evidence of increased economy-wide competition

An increase in the competitiveness of the US economy provides an alternative explanation for the change in the domestic level of idiosyncratic risk. Our contention is based on the idea that an ongoing fall in search costs as well as an increase in consumers' ability to direct business to different firms can produce a more competitive environment. London (2004) posits that increases in American competitiveness have greatly contributed to the growth in the US economy over the past 40 years. He argues that increased competition was driven by policies that enabled easier importation of products into the United States; deregulation of industries such as transportation, communication, and energy; effective enforcement of antitrust laws; and the decline of labor union power. London's thesis is similar to Blinder's (2000), except Blinder also attributes the increase in competitiveness to better alignment of shareholder and managerial interests. The Blinder (2000) and London (2004) claims of increased American competition are consistent with Bils and Klenow (2004), who provide empirical evidence of more competitive product pricing. Bils and Klenow (2004) report that the frequency of price changes is much higher



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in the mid-1990s than that in earlier published reports. Logically linked to competitiveness, price changes were most frequent for consumer nondurables and products that experienced higher introduction of substitutes, consistent with greater consumer choice in the recent economy. Chun et al. (2004) generally concur with our arguments and contend that the rapid diffusion of information technology plays a major role in the acceleration of Schumpeter's (1942) forces of creative destruction in the economy and the resulting increase in firm-level volatility.

### 4.6 The competitiveness explanation and other studies

The idiosyncratic risk literature has examined two broad areas: cross-sectional and time-series differences in idiosyncratic risk in the US markets, and cross-sectional differences among idiosyncratic risk levels in foreign markets. The competitiveness explanation, along with our findings of increases in fundamental idiosyncratic volatility, provides a new interpretation of these streams of literature.

Papers in the first stream of the literature have attributed the rise in idiosyncratic return volatility to other variables. For example, Brown and Kapadia (2007) show that initial public offerings have resulted in the listing of more volatile firms on exchanges. They argue that this trend explains much of the trend in idiosyncratic volatility. Bennett and Sias (2006) relate the increase in idiosyncratic volatility to the increased presence of small stocks. Our results show that these explanations only explain about 1/3 of the time trend of fundamental volatility, whereas competitiveness provides an explanation that can coexist with these studies and can explain the remaining increase.

The second stream of idiosyncratic risk literature investigates differences in cross-country levels of $R^2$s. These papers commonly attribute idiosyncratic risk levels to the efficiency of financial markets. Morck, Yeung, and Yu (2000) show that systematic risk and price synchronicity are higher in countries with poor corporate governance, even after controlling for obvious cross-country differences in industrial structure and economic activity. They argue that their findings are consistent with strong investor protection. Specifically, sophisticated investors have a lower incentive to impute firm-specific information in stock prices through their trading when investor protection is weak. Jin and Myers (2006) extend the Morck et al. (2000) argument by considering the effects of opacity on the relation between country-specific $R^2$s and corporate governance. They maintain that opacity is required to confirm the Morck et al. (2000) results because more opaque environments, combined with poor corporate governance, enable insiders to capture a larger proportion of the firm's operating cash flows. This leads to lower firm-specific risk for investors and higher country $R^2$s.

These papers provide tenable arguments for cross-sectional differences in the importance of idiosyncratic volatility in a particular country's market. Cross-sectional differences in legal environments can be obvious and noticeable,



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and they should have important effects. However, there are problems applying some of these ideas to the time-series trend in domestic idiosyncratic volatility, particularly in the past 20 years when the growth of idiosyncratic volatility has accelerated. It is doubtful that legal protection provided to investors in the United States has changed significantly in the past 20 years. We argue that domestic changes in the above set of cross-sectional explanations are unlikely to be sufficient, by themselves, to explain the increase in idiosyncratic volatility in the United States.

Carlin (2006) shows that firms can use opaqueness to create a less competitive product market. Countries with better information environments and better legal systems will have greater transparency, which makes it more difficult for firms to protect monopoly profits. Our exploratory findings in Table 11 lend support to the idea that competition is related to cross-country differences in idiosyncratic risk. Both the competitiveness explanation and Morck et al.'s (2000) trading-information hypothesis predict a relation between market opaqueness and idiosyncratic volatility. Competition is a broader explanation of cross-country differences in $R^2$s than the trading information explanation, since it is also consistent with differences in fundamental idiosyncratic risk.

## 5. Conclusion

This paper documents a significant increase over time in the idiosyncratic volatility of firm-level earnings, cash flows, and sales. Over the period 1964–2003, the magnitude of the increase in the idiosyncratic volatility of earnings, cash flows, and sales is large enough to explain why a rational stock market's idiosyncratic stock-return volatility has increased dramatically over the same period. We rule out the possibility that this finding is explained entirely by new listings, data provider coverage, higher proportions of smaller firms, changes in the composition of industries, or a general trend among firms toward focusing on fewer lines of business.

We explore the possibility that increased competition is the source of the increase in idiosyncratic volatility. We construct proxies for competition and conduct both cross-sectional and time-series tests. In support of our explanation, we find that return on assets, which is negatively related to idiosyncratic volatility in the cross-section, has declined over our sample period. Industry turnover, defined as the proportion of industry market value that enters and exits an industry in a given time period, is positively related to future idiosyncratic volatility. Further, the overall market has demonstrated an increase in industry turnover. We find a similar pattern in the market shares of foreign competitors. Cross-sectionally, firms in industries with more foreign competition experience more idiosyncratic risk, and time-series plots show that the level of foreign competition faced by the typical domestic firm has dramatically increased. Finally, since deregulation is associated with increased competition, we examine industries that have undergone significant deregulation. We find that deregulation

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is associated with significant increases in idiosyncratic volatility, even beyond the general time trend that we document. Examining cross-country trends in idiosyncratic volatility, we show that countries with greater growth in idiosyncratic stock-return volatility tend to have more competitive economies and undergo faster change in technological innovation. This mosaic of evidence lends support to the notion that economy-wide competition plays a role in the recent trend toward higher levels of idiosyncratic stock-return risk.

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