Alternative Explanations of the Volatility Trend: Are They Really That Different?

Abstract:
We study the puzzling behavior of the average level of individual stock return volatility around the turn of the millennium. The academic literature has proposed a host of putative explanations for the increase in volatility, which we consider in detail. The key advantages to our analysis are that: 1) we study all the major variables jointly, and 2) our analysis focuses on both the time-series and cross-sectional evidence. We find that turnover, which has curiously been ignored by the current literature, is quite useful in both the time-series and cross-section. The market-to-book ratio (which proxies for growth options) although useful in a time-series context lacks power in the cross-section, and some of the proxies used for other explanations proposed in the literature fail in the time-series once lagged volatility is introduced in the regression. Finally, it seems that all of the variables that track average volatility well do so mainly by capturing changes in the post-1994 period. These variables have no time-series explanatory power in the pre-1995 years.

JEL Classification: G32 G35

Keywords: Volatility, Trend, Turnover.

Date: March 18, 2008

I. Introduction

Campbell, Lettau, Malkiel, and Xu (2001) and Xu and Malkiel (2003) demonstrate that firm-level volatility exhibited an upward trend between the early 1960s and the late 1990s. This observation led to a flurry of research that has attempted to rationalize this trend. The overall conclusion from this subsequent research is that the change in volatility is explained by changes in the market capitalization of firms with different attributes including: the increased importance of Nasdaq firms and risky industries (Schwert, 2002; Bennett and Sias, 2006); the increased ownership of institutions (Xu and Malkiel, 2003); the younger listing age of a firm (Fink et al., 2006); the increased cash flow risk of newly listed firms (Brown and Kapadia, 2006); the increased uncertainty in profitability (Wei and Zhang, 2006; Pastor and Veronesi, 2006); the increased product market competition (Irvine and Pontiff, 2006); the increased level and variance of firm growth options (Hollifield, 2002, Cao et al., 2006); and the low stock price of many firms during speculative market episodes such as the one witnessed in the late 1990s (Brandt et al., 2005).

To understand the scope of the previous literature we list the variables used in these studies in Table 1. A common theme to these empirical investigations of the trend is their focus on changes in only one or two predictive variables. Each study concerns itself with a single facet and at best compares the ability of their chosen proxy with only one or two competing explanations. Despite there being many competing explanations proposed in the literature there has been little systematic effort to reconcile the various explanations. Noting that these various explanations are related—e.g. younger firms tend to be associated with more recent IPO vintages, be traded on Nasdaq, have high growth options, do not pay dividends, and have high volatility in cash flows—it seems natural to ask just how "different" the different competing explanations actually are. If one focuses on a single variable that is highly correlated with other conditioning variables one never knows whether or not the significance is the spurious result of omitted variables bias.

In Figure 1 we plot the market value-weighted average of quarterly volatility in the last 32 years. The variance of each stock in each quarter is estimated using the sum of squared daily returns within that quarter. The most striking observation from the figure is that the trend Campbell et al (2001) observed in the sample ending in 1997 is clearly a temporary "hump" in volatility at the turn of the Millennium, a point also observed by Brandt et al. (2005). Volatility since the start of 2004 seems to accord with historical norms. There appear to be three main episodes of abnormally high volatility: the 1974 OPEC oil crisis, an outlier in the fourth quarter of 1987 associated with the crash in October, and the aberrant behavior in volatility associated with the tech-bubble. The first two episodes and the "hump" at the end of the Millennium differ both in the length of the episode and magnitude of volatility elevation. Because the "hump" lasted for about a decade and the variation in volatility during this decade was particularly acute it seems clear that the significance of a particular proxy would predominantly depend on its ability to explain volatility behavior during this "hump" period. We thus pay particular attention to the run-up and subsequent drop in volatility around this episode in our empirical analysis.

We undertake an empirical study of volatility using both cross-sectional or panel regressions and time-series tests using weighted-average predictor variables.[1] To motivate the joint focus on the time-series and panel suppose that a particular firm characteristic is positively related to firm-level volatility. A systematic increase in that characteristic or an increase in the market capitalization of firms with high values of that characteristic will result in higher average volatility. For example, if younger firms tend to be more volatile a systematic decrease in the weighted-average age of firms (following an IPO wave or a shift in market capitalization towards young tech firms) will mean that the average age of firms in the market will be correlated with the average volatility level through time. It will also mean that the age of a firm will have cross-sectional explanatory power when comparing volatility levels across firms. Virtually all current theoretical arguments that are provided for the studies in Table 1 lend themselves to explanations about the difference in volatility levels between firms just as well as they do for a time-series explanation for the trend in the average volatility level in the market. By looking at these two dimensions jointly we provide a deeper analysis of the usefulness of the different proxies and explanations. Obviously we need both these features for a plausible explanation for the behavior volatility: the variable must explain volatility across different firms and the variable must also have changed through time. A variable that explains much in the cross-section but has not changed through time is of limited usefulness. Only a time-series analysis based on value-weighted averages of the variable and volatility can identify variation through time. On the other hand by focusing exclusively on the time-series evidence we lose a tremendous amount of useful information because we have relatively few observations (slightly over 120 quarterly

[1] We use the term cross-section somewhat loosely. We refer to our panel data firm-level analysis, which pools both time-series and cross-sectional data, a cross-sectional analysis to distinguish it from our pure time-series analysis that uses only the time series of cross-sectional value-weighted variables.

observations as opposed to tens of thousands of firm-quarters), and the time-series variables exhibit a high degree of correlation. Although some previous research has focused exclusively on either the cross-section (Xu and Malikiel, 2003; Pastor and Versonesi, 2003; Brandt et al., 2005; Bennett and Sias, 2006) or the time series (Cao et al., 2007), there are studies that consider both types of analyses (Wei and Zhang, 2006; Fink et al., 2006; Rajgopal and Venkatachalam, 2006; Brown and Kapadia, 2007; Irvine and Pontiff, 2007). Those studies that do include time-series regressions only include few variables.[2] This is unfortunate because the results may be due to an omitted variables bias since all of the time-series average variables used in these studies are highly correlated.

A contribution of our paper is that we include lagged volatility as an independent variable. These time-series regression tests regress a highly persistent variable (i.e. average volatility) on highly persistent variables (e.g. average age or book-to-market). In a simulation experiment we demonstrate that inference in this context suffers from a spurious regressions problem related to the work of Ferson et al. (2003). We find that using Newey-West standard errors, as is routinely done in the current literature, is an inadequate response to the problem of autocorrelated residuals that arises in this context. However, simply including lagged average volatility as an explanatory variable is successful in correcting the standard errors and thus inference in this context, and we demonstrate that its inclusion does little to erode the power of the tests.

We also include Turnover as yet another potential explanatory variable. Value-weighted average turnover is correlated with value-weighted averages of the other potential explanatory variables. Despite the rich literature that links turnover to volatility

[2] Rajgopal and Venkatachalam (2006) is the only paper to conduct a multivariate time-series with more than three variables (in their Table 4). However, the variables included in their analysis (except for market-to-book) are not those variables that are associated with the other explanations provided in the literature.

through information flow this variable has been virtually neglected by the volatility trend literature. Theoretical motivation for a positive relation between trading volume and return volatility dates back at least to Epps and Epps (1976), who show that price changes can be viewed as following a mixture of distribution, with volume being a mixture variable. Later studies focus on the relation between volume measures and adverse selections. In these models (e.g., Admati and Pfleiderer, 1988; Foster and Viswanathan, 1990) informed investors tend to trade at periods when their information advantage is greatest. This creates greater turnover levels at certain periods, which in-turn leads to a contemporaneous relation between price changes and volatility. Empirical work has routinely found that contemporaneous trading volume is closely linked with volatility. Given the extensive literature on the volume-volatility relationship it is curious that it has been overlooked in the current literature. In fact, the only paper who controls for turnover levels is Brown and Kapadia (2007), but it does so only in the cross-sectional analysis.

Our main empirical results can be summarized as follows:

1) Including lagged volatility is important both in the time-series and the cross-section regressions. In the time-series, it has a higher R-squared than any univariate regression using any of the other explanatory variables proposed in the literature.
2) Once lagged volatility is included in the time-series regression, many of the variables proposed in past studies fail to provide any contribution to the trend. These variables are associated with the following explanations: speculative episodes associated with low priced stocks (Brandt et al., 2005), institutional ownership (Malkiel and Xu, 2003), and volatility in fundamentals (Wei and

Zhang, 2006; Irvine and Pontiff, 2007).

3) Market-to-book, which Cao et al. (2007) use to proxy for growth options, is the single strongest variable in the time-series regressions (other than lagged volatility), but it has no explanatory power in the cross-sectional regressions.

4) The variables that do explain the time-series behavior in volatility (once lagged volatility in included) are Nasdaq classification (Schwertz, 2002); the age of the firm (Fink et al., 2006; Brown and Kapadia, 2007); dividend policy (Pastor and Veronesi, 2003); market-to-book (Cao et al. 2007); and turnover. A univariate time-series regression with any of these variables and lagged volatility yields somewhat similar results with an adjusted R-squared in the range 0.41-0.47. Also, the coefficient on lagged volatility drops by a third once any of these variables in included in the right-hand-side.

5) The variables that explain the time-series behavior in volatility (i.e., Nasdaq classification, age, dividend policy, market-to-book, turnover) are not able to explain the trend in the average volatility level in the pre 1995 period. Thus, it seems that the explanations are not able to describe the trend over the three decades, but rather these variables do a particularly good job in tracking the average level of volatility level during the "hump" period.

The remainder of the paper proceeds as follows. In Section II we discuss the previous literature in detail and discuss our empirical methodology. Section III discusses the problem of spurious regression and suggests a simple remedy. In Section IV we describe our data and the proxies that we use to compare past studies. Section V presents our cross-sectional panel regression results and Section VI the time-series results. We conclude in Section VII.

II Literature review and background

As outlined in Table 1, a host of explanations have been provided for the observed trend in volatility. The common theme to this research is that shifts in value-weighted volatility are because the number and/or relative market value of stocks with characteristics associated with higher volatility increased. In a rather early study, Schwert (2002) noticed that Nasdaq traded stocks exhibited an unusual degree of volatility during the late 90s, suggesting that the rising average volatility levels is related to the relatively high volatility of technology stocks. In the following years several studies used cross-section analysis to provide alternative perspectives on the volatility trend. Xu and Malkiel (2003) suggested that the increase in long-term growth rates and the increase in institutional ownership may have contributed to the increase in volatility levels. Pastor and Veronesi (2003) developed a model in which market-to-book, dividends, and age are inherently related as investors try to learn about a new firm's profitability. They show that non-dividend paying stocks are much more volatile than dividend payers. Brandt et al. (2005) find that the upward trend in volatility reverted in the years since 2002. They also show that high volatility stocks are predominantly low priced, which they interpret as evidence that the high volatility episode was due to a speculative episode driven primarily by retail investors. Finally, in a more recent cross-sectional study, Bennett and Sias (2006) show that much of the variation in volatility can be attributed to three "factors": the increased value of riskier industries, the increased number of small companies, and the level of concentration in the industry.

More recent studies have supplemented the cross-sectional analysis with a time-series analysis in which a certain average determinant is used to directly explain the trend in the average volatility level. Wei and Zhang (2006) show that the trend in average volatility is accounted for by the downward trend in ROE and the upward trend in the volatility of ROE. Fink et al. (2006) find that the systematic decline in the age of a typical public firm combined with the number of firms going public can explain a large fraction of the trend in average volatility. Brown and Kapadia (2007) show that over time, IPOs have been associated with riskier firms, and by controlling for IPO vintage (i.e., the decade in which the firm became public), one eliminates the trend of volatility. Rajgopal and Venkatachalam (2006) show that earnings quality is associated with the trend, while Irvine and Pontiff (2007) show that different measures of volatility in fundamentals are related to the observed trend. Finally, Cao et al. (2007), who conduct only a time-series analysis, show that market-to-book is a rather robust variable for explaining the trend, which they argue is consistent with the importance of growth options.

Note that the theoretical arguments behind the empirical analyses of the above papers could be used to describe a cross-sectional relation just as well as they are used to make a case for the average volatility trend. For example, if the increase in the average market-to-book ratio (which proxies for the average value of managerial growth options) is the reason for the observed trend in average volatility, then one should expect that firm-level market-to-book ratio (which proxies for the managerial growth options of a specific firm) will be correlated with volatility of a specific firm.

The common time-series behavior of average volatility and average values of conditioning variables can only be captured using time-series regressions. However, because these regressions are aggregate in nature they ignore much information available in a firm-level or cross-sectional analysis. To motivate the need for both a time-series and cross-sectional approach, consider the panel regression relationship which purports to explain firm-level volatility:

$$y_{it} = \alpha_i + \sum_{j=1}^{K} \beta_j X_{ijt} + e_{it}, \tag{1}$$

which holds for all i=1,…,N and t=1,…,T. If we define w_{it} as the relative market-weight of firm i at time t, the value-weighted regression of equation (1) obtained is

$$\begin{aligned} \bar{y}_t &= \sum_{i=1}^{N} w_{it} y_{it} = \sum_{i=1}^{N} w_{it} \alpha + \sum_{i=1}^{N} w_{it} \sum_{j=1}^{K} \beta_j X_{ijt} + \sum_{i=1}^{N} w_{it} e_{it} \\ &= \alpha + \sum_{j=1}^{K} \beta_j \bar{X}_{jt} + \varepsilon_t \end{aligned}, \tag{2}$$

where $\bar{y}_t = \sum_{i=1}^{N} w_{it} y_{it}$, $\bar{X}_{jt} = \sum_{i=1}^{N} w_{it} X_{ijt}$. The regression coefficients from both the time-series and cross-sectional regression are referring to the same concept. The advantage of the time-series test is that *only* the common trending behavior influences its estimates of the regression coefficient. On the other hand, because the number of firm-quarters is so much higher in the cross-sectional analysis, this regression will be more powerful. Both approaches are complimentary.

As we have previously noted the current literature initially used only a cross-sectional analysis, though more recent research typically uses time-series regression to directly study average volatility. Cross-sectional studies of volatility typically include a relatively large set of explanatory variables to avoid omitted variables bias. However, the time-series tests on average volatility only include one or two variables, typically, those variables that proxy for the explanation.[3] For example, Brown and Kapadia (2007) include 9 variables in their cross-sectional regression, but conduct a time-series test on average volatility with only the single explanatory variable, IPO listing vintage (and a time trend).

A possible reason for the use of only one or two explanatory variables in the time-series is the concern with the high correlation that exists between the different variables. This is a major concern especially because the number of observations is limited in the time-series analysis (one observation per period)[4] and one must be concerned about possible multicollinearity. In our empirical analysis we indeed find that the standard errors from the multivariate time-series regressions are higher than the univariate regressions, though there is still sufficient statistical evidence that some of the variables have explanatory power in a multivariate regression specification. The correlation between the variables is not surprising: if young firms tend to not pay dividends, be listed on Nasdaq, and have high market-to-book ratios—the value-weighted averages of these variables must be highly correlated. However, by focusing on a single regressor in the time-series tests there is a risk of spuriously inferring that a certain explanations is important, when alternative explanations provide comparable explanatory power.[5] Only by a multivariate time-series analysis using several value-weighted variables can we conclude which explanatory variables are more useful.

---

[3] Note that variables such as age and market-to-book, which feature in the later time-series work of Fink et al. (2006) and Cao et al. (2007) respectively, were considered in the (relatively) early cross-sectional regressions of Pastor and Veronesi (2003) and Wei and Zhang (2006).

[4] Note that many of the explanations rely on the quarterly data of Compustat, and some of the explanations lack the needed data if we go far enough back in time (e.g., Nasdaq firms' are relatively new and data availability starts in 1971). In our time-series regressions we have 128 quarterly observations.

[5] Most of the papers in Table 1 conduct a pooled regression analysis to show the dominance of their particular explanation. However, any pooled regression (firm-level) will mostly capture cross-sectional variation, and not time-series variation. We discuss this issue further below.

An important difference between our approach and the current literature (outlined in Table 1) is that we supplement the cross-sectional analysis with a time-series analysis that includes all the major variables used in past studies. Both the time-series and cross-sectional analysis are required: a cross-sectional analysis identifies variables that explain variation in firm-level volatility, while a multivariate time-series analysis provides evidence regarding those variables that can explain time-series variation in average volatility.

Finally we note that previous studies do not include lags of conditional volatility in their time-series regression tests, though Bennett and Sias (2006) include lag volatility in their cross-section analysis. This is curious given the high autocorrelation in volatility. In the next section we note that the high correlation induces a spurious regression problem that can be corrected by including lagged volatility as a regressor.

III. Spurious regression

It is well-known that volatility is quite persistent, and not surprisingly, so too is average volatility. One obvious concern is that the residuals from a regression of the level of volatility on explanatory variables will also be serially correlated. We find a first-order autoregressive coefficient of around 0.65 for the average volatility measure, which is quite persistent. Because of the residual autocorrelation most studies that use the time-series regression report Newey-West standard errors computed with a range of lags.[6]

In a simulation experiment Ferson et al. (2003) find that inference about return predictability is confounded by a spurious regression problem. They consider predictive

[6] Wei and Zhang (2006), Rajgopal and Venkatachalam (2006), Brown and Kapadia (2007) use three lags, Irvine and Pontiff (2007) use 8 lags with Yule-Walker correction, Cao et al. (2007) use 12 lags, and Fink et al. (2005) do not report the number of lags they use.

regressions in which the conditional mean varies linearly with an AR(1) predictor. When the R-square from this regression is at least 0.05 and the true explanatory variable is very persistent (i.e., an AR(1) coefficient greater than 0.95) the standard errors on irrelevant but similarly persistent explanatory variables are too low and these spuriously appear to be statistically significant. The problem is that the residuals are serially correlated and correcting the standard errors following Newey and West (1987) does not correct the problem.

Although our setup is slightly different because the independent variable in our time-series regression is highly persistent the residuals from simple OLS regressions are likely to be serially correlated. This is a problem for time-series studies of volatility dynamics because most previous studies regress average volatility on an intercept, a time trend and a few other explanatory variables (typically no more than three). To correct for autocorrelation they use Newey-West (1987) standard errors computed with between 3 and 12 lags. It is routine to think about volatility as an autoregressive process and yet none of these time-series studies include lagged volatility on the right-hand side of their time series regressions. Including lagged volatility has the potential to correct for the serial correlation in the residuals as the residuals from AR(1) models are serially uncorrelated.

To study the problem of spurious regression in our context we generate 1000 artificial sample paths of a time series X_t with $T = \{125,250,500,1000\}$ observations (our time-series sample is closest to 125) from an AR(1) model with autoregression coefficient of 0.66. We also generate an independent variable AR(1) random variable Z_t with equal persistence, which is thus completely irrelevant. The variance of both time series is normalized to unity, though this is without loss of generality. In each artificial sample we regress X_t on Z_t, computing standard errors in three ways: (1) OLS, (2) Newey-West with 3 lags, (3) Newey-West with 12 lags, recording the number of instances in which Z_t is significant at the 5 percent level. We report the percentage of significant observations in Panel A of Table 2. In sample sizes comparable with ours (i.e. 125 observations) we reject about 5 times too frequently at the nominal level using OLS standard errors, and even Newey-West standard errors with 12 lags we still reject almost 3 times more frequently than the nominal size. However, using Newy-West standard errors computed with 12 lags does seem to work in very large samples.

In Panel B we repeat the exercise including one lag of the dependent variable in the regression. We now find that the irrelevant regressor is not-rejected at about the appropriate size. Interestingly OLS has better finite sample properties in small samples. The relatively poor performance of Newey-West is because 12 lags is very long relative to the sample size of only 125 observations. In larger samples, Newey-West performs quite well. These results clearly identify the need to include lagged volatility on the right-hand side of the time-series regressions.

Of course by including lagged values of the dependent variable we might be sacrificing power by correcting the size this way. For example it is routine to run an OLS regression when testing for cointegration between persistent time series. To assess this issue we simulate data, Z_t and X_t, in which the conditional mean follows an AR(1) process:

$$\begin{aligned} Z_t &= X_t + e_t \\ X_t &= \phi X_{t-1} + u_t \end{aligned} \tag{3}$$

where $\phi = 0.66$, $\sigma_u^2 = \sqrt{1-\phi^2}$, and $\sigma_e^2 = (1-R^2)/R^2$. We then initially regress Z_t on a constant and X_t (computing the standard errors by OLS and Newey-West with both 3 and 12 lags) and then include lagged values of Z_{t-1}. Panels C through F of Table 3 present the fraction of statistically significant coefficients on X_t in the various specifications. These results suggest that there is virtually no difference between the power of the univariate regression and the regression including lagged dependent variables. This provides a strong rationale for including lagged volatility in the time-series regressions since its presence corrects the standard errors under the null of no predictability but does not erode the test's power.

IV Data

Because we are primarily interested in explaining the last decade of unusual volatility we select a wide range of potential explanatory variables. Because some relevant variables are only available for a short time period we face a tradeoff between having a very long sample with fewer variables or many variables over a shorter sample. To suitably balance these two concerns we use only data from Compustat, CRSP and Thomson Financial. As some of the explanations provided in the literature are highly overlapping (in the empirical sense), our guideline for selecting between alternative variables is to choose the variable that covers the largest number of firms. For example, we include volatility in profitability measures (Wei and Zhang, 2006) rather than cash flow volatility measures (Irvine and Pontiff, 2007) because it has fewer missing observations. We also omit variables that are based on very limited data sets (e.g., I/B/E/S or Zacks data set). To construct a volatility in profitability measure (Wei and

Zhang, 2006), we require financial information for the previous 12 quarters. As Compustat provides quarterly information starting 1970, our data includes all NYSE, AMEX and Nasdaq firms for which we have no missing values during the period 1973q1 to 2005q1.[7] In total, we have 246,607 firm-quarter observations.[8]

A. The dependent variable: Volatility

The dependent variable in our empirical analysis is average realized quarterly firm-level volatility. Because some explanatory variables we will consider in our empirical analysis are quarterly, we conduct a quarterly measure of volatility. We compute realized volatility as the sum of squared daily returns within a given quarter (see, e.g., Campbell et al., 2001). We note that some studies, e.g. Campbell et al. (2001), use idiosyncratic volatility. However, idiosyncratic and firm-level volatility are very highly correlated (which has been pointed out in the previous literature). We also note that although Campbell et al. (2001) find an upward trend in average idiosyncratic volatility they do not uncover such trend in the volatility of aggregate stock market returns., which suggests that the trend in idiosyncratic volatility should closely track total volatility. To ensure that the results are not driven by our use of total rather than idiosyncratic volatility, we repeat the analysis using idiosyncratic risk (from the market

[7] Two caveats to this criterion: (1) Thomson Financial data set starts at 1980. To avoid exclusion of this period, we set the institutional variable to zero during those years. Similarly, as CRSP does not classify firms to Nasdaq till 1983q2, we assume that all firms are Non-Nasdaq prior to that quarter.

[8] Since the number of firms in the 1962-1973 period is comparatively small and since most of the variation in volatility is in the last decade, we believe that differences in samples across studies are of minimal concern. In broad terms, it is fair to say that most of the studies in Table 1 include at least 90% of the market value of firms during those 3 decades. However, to make sure that this is indeed the case, we replicate Cao et al. (2007) with the full sample of firms (their original work does not include the financial services sector as these firms are theoretically less linked to growth options) and find that their results are robust for the full sample of firms. The only two studies which rely on a much smaller sample size are Xu and Malkiel (2003) and Rajgopal and Venkatachalam (2006).

model) following Campbell et al (2001) and find that the two volatility measures have a correlation coefficient of 0.99. We also produce idiosyncratic volatility measures of the three-factor model of Fama and French (1996) and find that it has a correlation of 0.96 and 0.97 with the two other volatility measures. The exceptionally high correlation suggests our results are not driven by our use of firm-level volatility.[9]

B. Nasdaq

Schwert (2002) documents that Nasdaq firms have shown a dramatic increase in volatility during the mid-late 90s. We therefore employ a **Nasdaq** indicator, which equals 1 if the firm is traded on Nasdaq, and zero otherwise.

C. Dividends

Pastor and Veronesi (2003) and Rubin and Smith (2007) show that firms that do not pay dividends have much more volatile returns. In fact, both studies show that dividend policy is the most significant determinant of volatility in the cross-section. We follow these studies and employ a **No dividend** indicator, which equals 1 if the firm did not pay a dividend during the quarter.

D. Age

Fink et al. (2006) argue that there has been a substantial increase in the fraction of young firms contemporaneously with the increase in idiosyncratic volatility. They focus primarily on the average age of a firm at the time of its IPO. They argue that in recent

[9] The analysis based on idiosyncratic volatility using both the market model and three-factor model are very similar and is available from the authors on request.

decades, and especially in the late 1990s, younger firms became public and coupled with the significant increase in the number of firms going public, it lead to a steady increase in idiosyncratic risk. Theoretically, the idea of age affecting volatility is supported by Pastor and Veronesi (2003) who claim that investors learn about firm's profitability over time. In a different study, Brown and Kapadia (2007) claim that it is not age itself that is important for volatility, but rather, firms that have been listed in more recent years are fundamentally riskier.[10] It is important in their analysis that firms from more recent IPO vintages exhibit persistently higher idiosyncratic risk than firms from earlier vintages. They claim that if firm age itself is important for volatility we should have observed a reduction in a firm’s volatility over time, as it grows older over time. However, they do not find evidence of a meaningful or consistent decline in volatility for IPO listing vintage groups over time. An alternative explanation for this empirical observation is that the marginal contribution of a single year to the age of a firm is important only in the first few years post-IPO, when the investing public is not familiar with the company. Because Brown and Kapadia (2007) partition firms to 10 year segments based on IPO vintage, they may miss the resolution of the age variable where it matters most, i.e. when firms are very young. Further, as we observe in Figure 1, most of the variation in volatility occurs during the years 1995-2004. During that period the number of new listed firms increased (and then decreased) dramatically so both the average firm age and the value of the 1995-2004 IPO vintage will be highly correlated. To include the finding of both papers, our **Age** variable is the number of years since the firm appears on CRSP and we Winsorize our age variable at 30 years, as the marginal effect of a year for older firms is

[10] Empirically, Brown and Kapadia (2007) show that 5 dummy variables of IPO vintage decades drive out age in the cross-section.

limited.[11]

E. Earnings and earnings volatility

Wei and Zhang (2006) claim that changes in earnings fundamentals may be the reason behind the increase in idiosyncratic volatility, which Irvine and Pontiff (2007) claim is attributed to more intense economy-wide competition. Both papers produce somewhat different proxies for volatility in fundamental cash flow; however, they both rely on data from the 12 previous quarters. Because Wei and Zhang's (2006) measure has fewer missing observations we follow their methodology. They show that stock return volatility is negatively related to the return on equity (**ROE**) and positively related to the volatility of profitability (**VOLP**). We follow Wei and Zhang (2006) in calculating VOLP based on the previous 12 quarters ROEs, and Winsorize the firm-level ROE observation at -0.5 and 0.5.

F. Share price

Brandt et al. (2005) find a strong cross-sectional relation between low priced stock (i.e., stocks of less than $10) and idiosyncratic volatility. They suggest that volatility tends to elevate during episodes of euphoric bull markets with record price-fundamental multiples. They suggest that during these speculative episodes investors are particularly attracted to low priced stocks, which leads to a strong correlation between share price and return volatility. We thus use a **Low price** indicator for firms whose price

[11] Note that Fink et al. (2006) and Brown and Kapdia (2007) measure age as the year of either founding or incorporation, while Pastor and Veronesi (2003) measure age as the number of years since the firm appears on CRSP. We find that the two measures are highly correlated (0.89), and that the way age is measured does not alter the results.

is less than $10 at the end of the quarter.

G. Growth options

Cao et al. (2007) establish a theoretic link between idiosyncratic risk and growth options available to managers. While they motivate their analysis by managers desire to increase the value of the equity by taking more idiosyncratic risk when these options are available; empirically, it would be hard to distinguish between a managerial growth option explanation and a simple change in long term growth (Xu and Malkiel, 2003). To illustrate this point, consider the market-to-book ratio, which is Cao et al.'s (2007) preferred proxy for managerial growth options. According to the Gordon growth model, the value of a share is given by

$$P_0 = \frac{d_0(1+g)}{r_e - g}, \tag{4}$$

where d_0 is the current dividend, r_e is the required return on equity and g the expected growth rate of the firm's dividends. Since dividends paid can be represented as the return on equity multiplied by the payout ratio, the market to book ratio can be represented as

$$\frac{P_0}{B_0} = \frac{ROE \times payout\ ratio \times (1+g)}{r_e - g} \tag{5}$$

where B_0 is the book value of equity, and ROE is net income divided by equity. Even if we assume a fixed r_e (i.e., as we are focusing our attention on idiosyncratic volatility), we must be cautious in interpreting what market-to-book is proxying for, as it is a combination of dividend policy (payout ratio), profitability (ROE), and expectations on growth (or alternatively availability of growth options). Unfortunately the link between the theoretical motivation (i.e. managerial growth options) and the empirical support becomes unclear when market-to-book is used to track changes in volatility levels. Further, as capital expenditure, an alternative proxy used by Cao et al. (2007) for growth options, does not track volatility well, it is hard to interpret these results.[12] We use in our analysis the market-to-book measure (**Maba**) and calculate it following Appendix B of Cao et al. (2007).

H. Regulated industries

One possible explanation for the change in volatility may be changes in the composition of industries, which is referred to in Bennett and Sias (2006). While to some extent this change is captured by Nasdaq, we also employ a **Not regulated** indicator for firms that are classified in non-regulated industries (first SIC digit is not 4 or 6). We choose this variable because regulated stocks are significantly less volatile than non-regulated firms.

I. Institutional ownership

Another possible explanation for the change in volatility may be the increase in the level of institutional ownership that has occurred in the last decade. Xu and Malkiel (2003) claim that institutions may have common sentiments and their interpretation of news may lead to similar buy/sell decisions. If that is the case, when institutions hold a larger fraction of the market, they may contribute to volatility. **Institutions** is defined as the fraction of institutional ownership of the firm's share at the end of the quarter.

[12] We use capital expenditure both in the cross-section and time-series. Since capital expenditure is missing for many firms, using it in the analysis reduces the sample and we do not report the results here. However, capital expenditure is not significant in the cross-section and the time-series (once lagged volatility is included).

J. Turnover

We supplement the variables discussed above, which have all been considered in the literature, with an additional variable that has been ignored but is nonetheless crucial for studying volatility: turnover. The relationship between trading volume (or turnover) and price volatility is well documented. In 1987, Karpoff (1987) discusses 19 articles studying this empirical link. The information flow induced volume-volatility link has been motivated theoretically by Epps and Epps (1976), Tauchen and Pitts (1983), Admati and Pfleiderer (1988) and Foster and Viswanathan (1990). Some of the more recent empirical studies include Lamoureux and Lastrapes (1994), Richardson and Smith (1994), Foster and Viswanathan (1995), and Fleming, Kirby and Ostdiek (2006). Curiously, despite the rich theoretical and empirical literature on the role of trading volume on volatility it has been essentially ignored in the debate about idiosyncratic volatility at the turn of the Millennium. This omission is important because the common explanatory variables are correlated with turnover, and their significance may be due to an omitted variables bias. In fact the only paper in this literature that uses turnover in the analysis is Brown and Kapadia (2007) but they do so only in the cross-section. We rectify this oversight and include turnover as a putative explanatory variable, alleviating concerns that previous results may be resulting from an omitted variables bias.[13] We define the variable **Turnover** as the average monthly turnover in the firm's stock in a

[13] We also note that some other explanatory variables can be indirectly motivated by turnover. For example, Campbell et al. (2001) discuss the contemporaneous increase in the level of institutional ownership and idiosyncratic volatility in terms of common trading behavior and the increase in day trading as potential explanations. Similarly, firms that have more uncertainty about future profitability tend to have higher turnover levels since there is more heterogeneity in beliefs about their future performance (Harris and Raviv, 1993; Kraus and Smith, 1996). Therefore, we can also motivate turnover as a control variable.

given quarter.

V. Cross-sectional analysis

We start our analysis of the cross-sectional determinants of volatility using a panel regression approach. As noted above, we are particularly interested in understanding the curious behavior in the late 1990s. We therefore partition our sample into two sub-periods: the period before 1995 and the period after 1994. We choose to partition the sample at the start of 1995 because it appears from Figure 1 to be around the time where the "hump" begins. Also, our sample ends in the first quarter 2005, which gives exactly 10 years of data in the post-1994 era. Varying the quarter we partition on does not materially affect our results.

Table 3 presents some descriptive statistics of the dependent and independent variables during the two sub-periods. We observe that quarterly volatility levels increased from a median of 3% in the pre-1995 period to a median of 5% in the post-1994 period. Interestingly, there is no apparent change in the standard deviation in volatility between the two sub-periods. Other changes in firms' characteristics are also observed in the table. Turnover levels have more than doubled, increasing from a median of 34% to a median of 71%. The median age (recall that we Winsorized at 30) had decreased from 14.3 years to 11.1 years. Thus it appears that the increase in IPO activity reduced the average age of listed firms. Maba has also increased by about 20% from a median of 1.13 in the pre-1995 period to a median of 1.33 in the post-1994 period. There are also clearly evident changes in ROE and VOLP. There seems to be dramatically more variation in these two variables in the post-1994 period as compared with the pre-1995 period. Finally, the increase in institutional ownership is substantial, increasing from 17.62% in the early period to a level of 40.26% in the post-1994 period.

Regarding our indicator variables, we observe that the number of Nasdaq traded stocks has increased dramatically. While these represent only 24% of sample of firms in the pre-1995 period, they constitute 53% in the post-1994 period. Similar to Fama and French's (2001) observation, we find that non-dividend paying firms constitute 60% of the sample firms in the post-1994 period. There are also almost twice as many low priced stocks in the post-1994 period as compared with the pre-1995 period, while the percentage of non-regulated firms seems to have somewhat decreased over time.

Taken together, the summary statistics indicates that all of the characteristics, with the possible exception of the number of non-regulated firms, have changed dramatically. Further, the directions of the changes in all the variables, except for the number of regulated industries, are in the right direction to provide a reasonable explanation for the increase in volatility.

We next turn to the correlation coefficients between the different explanatory variables used in the study. We calculate the correlation coefficients for the pre-1995 and post-1994 period separately, and present the average and standard deviation of correlations for each of the sub-samples. The correlations are calculated every quarter and standard deviations (in parentheses) are calculated across the quarters in the sub-sample. Below the diagonal we present averages of correlation for each pair of variables in the pre-1995 period, while above the diagonal we repeat the calculation for the post-1994 period. In Table 4 we can observe that for both sub-periods, the pair-wise correlation coefficients have predominantly the same sign in the two sub-samples;

however the magnitude of the correlation have changed in a few cases. In particular, when we look at the volatility row and column, the signs of the correlation is always the same; however, there are sizeable changes for some of the pairs. The non-regulated dummy positive correlation with volatility has increased in the post-1994 period compared to pre-1995 period, suggesting that non-regulated firms have become more volatile over time. We observe a similar pattern among Nasdaq firms. Interestingly, the market-to-book ratio is essentially not correlated with volatility in pre-1995 period, but has a moderate correlation with volatility in the post-1995 period. Finally, the high absolute correlation of turnover, age, the no dividend dummy, and VOLP with volatility seem to be a rather persistent attribute of the data. Thus, even though we had observed major changes in many of the explanatory variables over time, we learn that the variables that are highly correlated with volatility (in absolute value) are rather stable through.

Table 5 provides cross-sectional regressions for the two sub-periods. We normalize all our variables so the coefficients can be interpreted as the number of standard deviations change in response to a one standard deviation change in the independent variable. Because the dependent volatility is heavily skewed (the skewness statistic is 82.66) we use as the dependent variable the natural log of volatility. Apart from the explanatory variables described in the previous section, we also control for **Size** (the market value of the firm's equity). Because market value is also somewhat skewed (skewness of 16.58), we again take its log. Because volatility is very persistent we include the lag of the independent variable (**Lag volatility**) as an independent variable. All independent variables are from the previous quarter (i.e., lagged), except for turnover, which is a flow variable.[14] We consider a range of regression specifications. In specifications (1a), (2a), and (3a) we use firm and quarter fixed-effect regressions, while in specifications (2a), (2b), and (2c), we follow Petersen (2007) and apply the double clustered standard errors, which correct for both time and firm dependency.

A number of key results emerge from Table 5. Although the statistical significance of the coefficients varies slightly between specifications, both specifications provide similar interpretations. While this result may not be terribly surprising given that our sample is so large, we stress that the results suggest that the fixed-effect regression may be driven by cross-sectional differences rather than by changes through time.[15] Further, the results in both sub-periods are quite similar, suggesting that the importance of the variables for explaining volatility in the cross-section has not changed dramatically over time. The most important explanatory variable is lag volatility, which explains about 35% of the variation in volatility in the fixed-effect specifications and about 60% of the variation in the clustered errors specifications. Also, the coefficient of lagged volatility is more statistically significant than any other coefficient. Turnover is the second most robust variable. It accounts for about 15-20% of the variation depending on the time and specification. The third most significant coefficient is the low price indicator, which accounts for an average of 10% of the variation in volatility. Size also accounts for an average of 10% of the variation in volatility, but its coefficient is much less significant than that of low price, turnover or lag volatility. The coefficients of age, no dividend, and Nasdaq are also significant (with the expected sign) but seem to jointly explain less than

[14] The qualitative nature of the results is not affected by using the contemporaneous explanatory variables.
[15] Though the fixed-effect specification of Table 5 provides slightly different estimates, the sign and significance of the coefficients yield essentially the same results as the double clustered or Fama-McBeth (1973) specifications (not provided, but available from the authors on request).

10% of the variation in volatility. Also, the Nasdaq coefficient is much more significant in the post-1994 period than in the pre-1995 period. Volatility in fundamentals, which is represented by the coefficients of ROE and VOLP, also explains some of the variation in volatility, and both coefficients are very significant (with the expected sign). As one may expect, non-regulated firms seem to exhibit a somewhat higher volatility level, but the coefficient is not significant in the pre-1995 period when using the fixed-effect specification. Finally, in both sub-periods, the coefficient of Maba is negative and statistically significant in the fixed-effect specifications, and is positive but insignificant in the clustered errors specifications. These results indicate that market-to-book is not an important variable for explaining firm-level volatility in the cross-section. We also find that institutional ownership is negatively correlated with volatility, which is counter to the small S&P 500 sample results of Xu and Malkiel (2003).[16]

Summarizing the results of Tables 3, 4, and 5, we find that the relation between the different variables and firm-level volatility is persistent across the different methodological approaches and different time periods. We find that most of the explanations provided in the literature provide some explanatory power over and above lagged volatility; though, the coefficient of lagged volatility is the most significant. We find that turnover is the second most robust variable and the low price indicator is the third most robust variable. Other variables that are consistent with their respective explanation include: age, no dividend, Nasdaq, VOLP, ROE, and not-regulated. We find that the coefficients on Maba and institutions are either negatively significant or not

[16] We note that Xu and Malkiel (2003) only controlled for size in their cross-sectional analysis. To make sure that the negative coefficient of institutions is not caused because of the zero value in the pre 1980 years, we rerun the first sub sample period excluding the observation that pre date 1980. The point estimate on institutions' coefficient is similar in magnitude and sign.

significant, which is counter to the explanations provided by Cao et al. (2007) and Xu and Malkiel (2003) respectively.

Note that although the cross-sectional analysis indicates the importance of the different variables in determining firm-level volatility, it is unable to identify which variables are responsible for the time-series behavior of volatility. Most of the variables provide similar explanatory power in both sub-samples, and both have changed over time. Further, as there is a high correlation between the different explanations, a careful time-series analysis is necessary.

VI. Time-series analysis

It is important to note that panel-regression results are mainly driven by cross-sectional variation and this cross-sectional variation will also tend to appear in firm fixed-effect regressions, as cross-sectional differences may not be constant through time. This means that even if a certain correlation between a variable and firm-specific volatility is uncovered, this does not imply that this variable is responsible for the overall trend in volatility.

Our approach therefore is to track changes in aggregate volatility with changes in aggregate measures. Previous studies following this approach (Fink et al., 2006; Wei and Zhang, 2006; Brown and Kapadia, 2007; Cao et al., 2007; Irvine and Pontiff, 2007) are almost always univariate in nature. The content of such a univariate analysis is also contained in the simple time-series plots of the underlying variables. Furthermore, given the high correlation between the alternative conditioning variables we must be cautious in interpreting the results because of potential omitted variables bias. In contrast, we employ a multivariate analysis and compare these results with the univariate estimates.

We aggregate all our variables following the Campbell et al (2001) methodology. Value-weighted measures are computed as[17]

$$VW_t = \sum_{i=1}^{N_t} w_{it} m_{it} , \qquad (3)$$

where VW_t is the aggregated value-weighted measure at time *t*, w_{it} is the weight of firm *i* at the end of quarter *t*-1 (measured in terms of market value), m_{it} is the measure of firm *i* calculated during quarter *t* or at the end of quarter *t* depending of the type of measure (i.e. stock or flow), and N_t denotes the number of firms at time *t*. The indicator variables we employed in the cross-section analysis lend themselves to easy interpretation when value-weighted. Nasdaq translates to the market portion (percentage) attributed to Nasdaq traded firms. The no dividend indicator translates to the market portion (percentage) attributed to non-dividend paying firms; the low price indicator translates to the market portion (percentage) of firms whose price is less than $10; and the not regulated indicator translates to the market portion (percentage) of firms classified to non-regulated industries.

A. Time-series evidence

In Panel A of Table 6, we compute the sample mean and standard deviation for the value-weighted sample in the pre-1995 and post-1994 sample periods. Similar to the results in the cross-section, the average level of volatility is much higher in the post-1994 data—being nearly twice the size. Similarly to the cross-sectional distribution of Table 3,

---

[17] We compute value-weighted volatility following Campbell et al (2001). An advantage of using value rather than equal weights is that value-weighted averages are less susceptible to outliers in the data.

we observe that the level of many of the variables is very different in the later period than in the earlier period. In particular, all of the variables with the exception of age, ROE, not regulated stocks, and low price – exhibit very large changes. The lack of real change in the market value of low priced stock is particularly interesting (increased from 1.86% to 2.06%) because Table 3 revealed that the *fraction* of low priced stocks has increased dramatically (from 27% of the sample in the pre-1995 period to 47% of the sample in post-1994 period). This suggests that the speculative episode explanation may not be relevant to the trend in value-weighted volatility.

Figure 1 plots the time series of value-weighted volatility. It is clearly apparent that the volatility trend documented by Campbell et al (2001), whose data terminated in 1999, was actually a "hump" around the turn of the Millennium. In Figure 2 we plot the time-series of each value-weighted average of the ten conditioning variables of interest. The most striking observations are the high correlation between many of the variables. This is born out by the sample correlation of the value-weighted variables in Panel B of Table 6. While the cross-sectional correlations between the variables are not terribly large (in absolute value), we do observe large correlations between many of the value-weighted variables (in absolute value). The correlation between the different explanatory variables and turnover is particularly high. Except for ROE and low price, turnover has a correlation of about 0.7 or above (in absolute value) with any other explanatory variables. Most relevant for the attempt to explain the volatility "hump" is the peak around 2000-2001 evident in Figure 2 in the time-series of Turnover, Maba, NASDAQ, no dividend, and age (where, we can observe a corresponding dump in 2000-2001) variables. This high correlation between the different explanatory variables calls for caution in interpreting the results from time-series tests, as it raises concerns about both multicollinearity and omitted variables bias. Figures 1 and 2 also clearly identify the radically different behavior of many aspects of the stock market in the late 1990s and early part of the new Millennium.

In Table 7 we report the results of a regression of value-weighted average volatility on a range of conditioning variables. Similar to the cross-section analysis, all explanatory variables are lagged one quarter, except turnover, which is a flow variable.[18] We first run univariate regressions on each of the ten explanatory variables and then a multivariate regression using all variables jointly. The Durbin-Watson statistic is recorded in the last row of the table and all models exhibit strong positive serial correlation (i.e. the DW statistics are less than 2), suggesting miss-specification. To account for this serial correlation we compute the standard errors following Newey and West (1987) using 3 lags (recall we are using quarterly observations). The fit of the univariate regressions as measured by adjusted R-squared vary substantially. The best fit is Maba which generates an R-squared above 34 percent. This result is similar to that of Cao et al. (2007). Three other variables do a moderately good job in explaining the trend: turnover, age and no dividend, whose regressions have an adjusted R-squared of around 25 percent. Other variables have a much lower adjusted R squared and/or produce results that are inconsistent with their theoretical motivation. ROE is able to explain only 5% of the variation and has a positive and statistically significant coefficient, which is counter to the explanation that higher ROEs should reduce volatility. VOLP is only marginally significant with *t*-statistics less than 2. Similarly, the value of non-regulated firms is

[18] The results reported are basically unchanged if one runs the regression with the contemporaneous variables, as all of the variables (except turnover) are highly persistent.

negatively correlated with average volatility, which again goes counter to common intuition. The low price variable, which had much explanatory power in the cross-sectional regression, has zero explanatory power in a time-series context; illustrating the advantage of a joint cross-sectional and time-series analysis. The institutional ownership coefficient has the right sign, but a relatively low adjusted R-squared of around 5 percent. This result, taken together with the negative correlation we found in the cross-section regressions, suggests that institutional ownership cannot account for the trend. The multivariate regression produces an impressive adjusted R-squared of over 60 percent; however, we must be cautious in interpreting the results because of concerns about multicollinearity. Note that the coefficient of Nasdaq, no dividend, not regulated, and institutions flip sign, suggesting that there may be some omitted variables bias in the univariate results. Interestingly the point estimate and statistical significance of turnover increases in the multivariate regression (the coefficient increases from 0.0283 to 0.1035 and the *t*-statistic increases from 2.7 to 6.6), suggesting that turnover is a particularly important determinant for the trend. We also note that the significance of Maba is reduced in the multivariate regression: the *t*-statistic decreases from 4.3 to 2.7.

To future address the issue of serial correlation we include a lag of average volatility in the regression, whose results we report in Table 8.[19] Note the dramatic reduction in serial correlation as the DW statistics are quite close to 2, particularly in the turnover and full-blown multivariate specifications. The R-square of the base AR(1) model (the first column) is 38 percent, exceeding all of the previous univariate regressions. Interestingly we find a dramatic increase in the model fit after adding the

[19] Following the results of our simulation experiment reported in Section III, we compute the *t*-statistics using OLS standard errors.

predictors. The best fitting individual explanatory variables is Maba with an adjusted R squared of 47%, followed by turnover with an adjusted R-squared of about 44 percent. We also observe that after the inclusion of lagged volatility, the coefficient of the variable VOLP, which was marginally significant in Table 7, is not significant in Table 8. However, age, no dividend, and Nasdaq remain significant (with the correct sign), and yield similar adjusted R squared in the range of 41-42%. The results with regard to the full-blown regression are similar to those reported in Table 7. Interestingly after including all variables the point estimate of turnover increases more than six-fold from 0.0158 to 0.0956 and the *t*-statistic doubles, while the Maba *t*-statistic drops from 4.9 to 3.4, and the lag volatility *t*-statistic drops from 8.8 to 3.1. We also observe that accounting for turnover, age, dividend policy, Nasdaq, and market-to-book causes a dramatic decrease in the coefficient on lagged volatility (decreasing from about 0.6 in the univariate to around 0.4 in the bivariate regressions), though the other variables (i.e. volatility of profitability, ROE, regulated dummy, institutions, and price) do not affect the autocorrelation coefficient.

A quick perusal of Figure 1 leaves no doubt that October 1987 is an outlier. Because the number of observation in the time-series analysis is relatively small (128 observations), we want to make sure that this outlier does not drive our results. Therefore, as a robustness check, which we do not tabulate, we allow the intercept to differ in Q4-1987 and rerun the specification of Table 8. While the R-squared of all the specifications increase substantially (i.e. Maba and turnover regression yield an R-squared of 64% and 69% respectively), there seems to be little difference in terms of the interpretation of the results.

Finally, we also account for a possible break in the relationships between the variables in 1995. We allow for the intercept and the coefficients on all parameters to change after the end of 1994. The parameter estimates are reported in Table 9. For each model specification we report the estimate pre-break in the first column, and the change in the parameters post-break is reported in the second column. In the interest of saving space, we report the results for the two most robust variables in the time series (i.e., turnover and Maba) and a full blown regression specification.

Given the "hump" in the last decade, it should not be surprising that one can reject the null hypothesis of no-structural break.[20] We observe that the coefficients on both variables are significant in the post 1994 period, but are insignificant in the pre-1995 period. These results persist no matter whether you include lagged volatility in the specification or not. While not reported, we find that the coefficients of other variables that track average volatility well (i.e., Nasdaq, no dividend, and age) are significant in the post-1994 period but not in the pre-1995 period. It seems that the "hump" in volatility is an unusual period, when many firm characteristic were associated with changes in volatility. Thus, one cannot escape the conclusion that the different explanations provided in the literature are essentially capturing the variation in volatility during the last decade rather than being explanations of the trend in volatility over the three decades.

Comparing the importance of turnover and Maba, turnover seems to track volatility marginally better as in the lagged volatility specification it produces an adjusted R-squared of 49%, while the turnover specification provides for an adjusted R squared of 46%. Turning to the interpretation of the parameters themselves we note in the last 2 columns of Table 9, which report the multivariate tests, that Maba is no longer

[20] To conserve space we omit the tests but these are available from the authors on request.

statistically significant. We reiterate that because there is such high correlation between the explanatory variables we have a trade-off between a univariate regression analysis that suffers from omitted variables and a multivariate regression analysis that suffers from the high correlation between the independent variables (and the high standard errors associated with it). We therefore should exercise caution when interpreting the multivariate regressions. However, it seems that turnover is marginally more important for explaining the trend as its positive correlation with average volatility "survives" the full blown regression specifications even though lag volatility is completely driven out, and many of the other variables, who in the univariate specifications are correlated with the trend (age, no dividend, Nasdaq, maba, VOLP), either flip sign or become insignificant (the age variable stays marginally significant).

VIII Conclusions

We have studied the curious behavior of volatility during the turn of the Millennium. Contrary to the current literature, which has proposed many explanations to the trend in volatility, we concentrate our effort on empirically testing the relevance of the major proxies used in past studies. We conduct both a cross-sectional and time-series analyses as a particular proxy should be (a) related to firm-level volatility, and (b) have changed significantly over time to produce the trend in average volatility. We also note that previous time-series regression tests have not included lagged volatility as a conditioning variable. We demonstrate that the persistence in volatility creates a spurious regression problem, which can be overcome by including lagged volatility on the right hand side. We find that some of the variables that one may associate with the tech-bubble are important both in the time-series and cross-section analysis (e.g., Nasdaq classification indicator, dividend payment indicator, age), some are useful only in the cross-section (e.g., ROE, VOLP, and low price indicator), and some are useful only in the time-series (market-to-book).

Our analysis includes the variables that have been proposed in the existing literature, and we have added one other important variable: turnover. Despite the extensive literature on the link between turnover and volatility, changes in turnover levels have been ignored as an explanation for the volatility dynamics. We find that turnover is useful both in time-series and cross-sectional regressions.

Finally, our time-series analysis suggests a structural break around 1995, which lead to an unusual "hump" in both volatility and many firm characteristics that are related to the technology run up and following melt down. These characteristics are not useful in explaining changes in volatility levels in the pre-1995 period, which leads us to suspect that all explanations and proxies (including our turnover variable) are associated with the unusual "hump" in volatility in the turn of the Millennium.

References

Admati, A.R., and P. Pfleiderer, 1988, A theory of intraday patterns: Volume and price variability, Review of Financial Studies 1, 3-40.

Bennett, J., and R. Sias, 2006, Why company-specific risk changes over time, Financial Analysts Journal 62, 89-100.

Brandt, M.W., A. Brav, and J.R. Graham, 2005, The idiosyncratic volatility puzzle: Time trend or speculative episodes, Working paper, Duke University.

Brown, G., and N. Kapadia, 2007, Firm-specific risk and equity market development, Journal of Financial Economics 84, 358-388.

Campbell, J., and M. Lettau, B. Malkiel, and Y. Xu, 2001, Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk, Journal of Finance 56, 1-43.

Cao, C., T.T. Simin, and J. Zhao, 2006, Can growth options explain the trend in idiosyncratic risk? Review of Financial Studies, forthcoming.

Epps, T., and M. Epps, 1976, The stochastic dependence of security price changes and transaction volumes: Implications for the mixture-of-distributions hypothesis, Econometrica 44, 305-321.

Fame, E. F., and K. R. French, 1993, Common risk factors in returns of stocks and bonds, Journal of Financial Economics 33, 3-56.

Fama, E. F., and K.R. French, 2001, Disappearing dividends: changing firm characteristics or lower propensity to pay? Journal of Financial Economics 60, 3-43.

Fama, E., and J. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, Journal of Political Economy, 81, 607-636.

Ferson, Wayne E., S. Sarkissian, and T.T. Simin, 2003, Spurious regressions in financial economics? Journal of Finance 58, 1393-1413.

Fink, J., K.E. Fink, G. Grullon, and J. Weston, 2006, Firm age and fluctuations in idiosyncratic risk, Working Paper, Rice University.

Fleming, J., C. Kirby, and B. Ostdiek, 2006, Stochastic volatility, trading volume, and the daily flow of information, Journal of Business 79, 1551-1590.

Foster, F.D., and S. Viswanathan, 1990, A theory of the interday variations in volume, variance, and trading costs in securities markets, Review of Financial Studies 3, 593-624.

Harris, J., and A. Raviv, 1993. Differences of opinion make a horse race. Review of Financial Studies 6, 473–506.

Hollifield, B., 2002, Comment on: Stock volatility in the new Millennium: how wacky is Nasdaq? Journal of Monetary Economics 49, 27-30.

Irvine, P., and J. Pontiff, 2007, Idiosyncratic return volatility, cash flows, and product market competition, Review of Financial Studies, Forthcoming.

Karpoff, J., 1987, The relationship between price changes and trading volume: A survey, Journal of Financial and Quantitative Analysis 22, 109-126.

Kraus, A., and M. Smith, 1996. Heterogeneous beliefs and the effect of replicatable options on asset prices, Review of Financial Studies 3, 723–756.

Lamoureux, C., and W. Lastrapes, 1994, Endogenous trading volume and momentum in stock-return volatility, Journal of Business and Economic Statistics 12, 253-260.

Newey, W.K., and K.D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, Econometrica 55, 703-708.

Pastor, L., and P. Veronesi, 2003, Stock valuation and learning about profitability, Journal of Finance 58, 1749-1789.

Petersen, M., 2007, Estimating standard errors in finance panel data sets: comparing approaches. Forthcoming, Review of Financial Studies.

Richardson, M., and T. Smith, 1994, A direct test of the mixture of distributions hypothesis: Measuring the daily flow of information, Journal of Financial and Quantitative Analysis 29, 101-116.

Rajgopal, S., and M. Venkatachalam, 2006, Financial reporting quality and idiosyncratic volatility over the last four decades, Working paper, University of Wahsington.

Rubin, A., and D.R. Smith, 2007, Volatility, dividends and institutional Ownership, Working paper, Simon-Fraser University.

Schwert, G. W., 2002, Stock volatility in the new millennium: How wacky is Nasdaq? Journal of Monetary Economics 49, 3-26.

Tauchen, G.E. and M. Pitts, 1983, The price variability-volume relationship on speculative markets, Econometrica 51, 485-505.

Wei, S. and C. Zhang, 2006, Why did individual stocks become more volatile? Journal of Business 79, 259-291.

Xu, Y., and B. Malkiel, 2003, Investigating the behavior of idiosyncratic volatility, Journal of Business 76, 613-643.

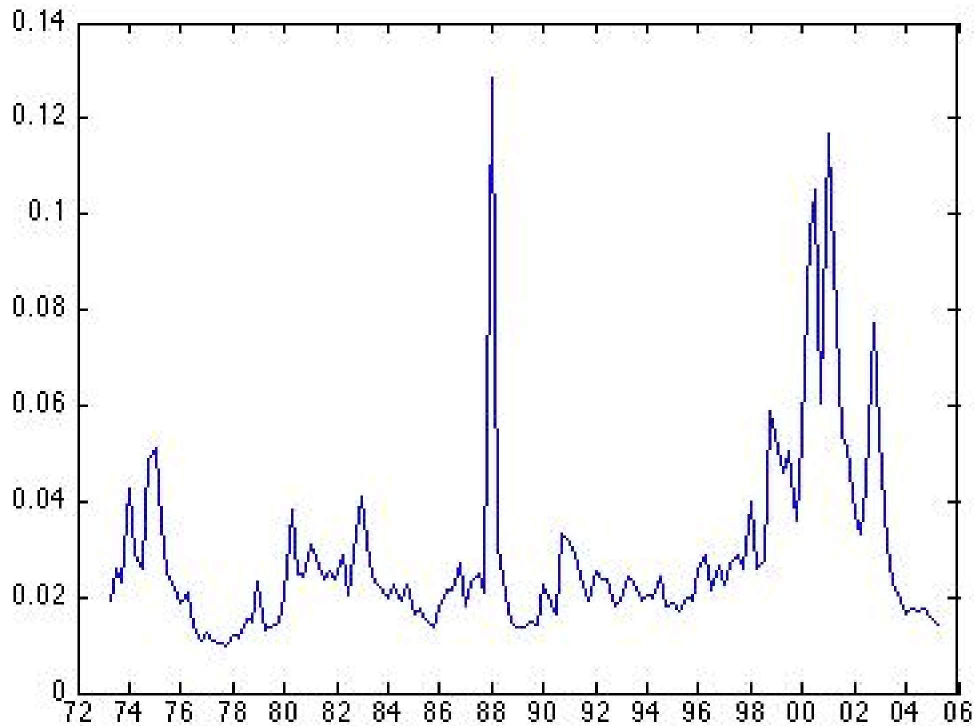

Figure 1: Plot of annualized value-weighted average quarterly volatility.

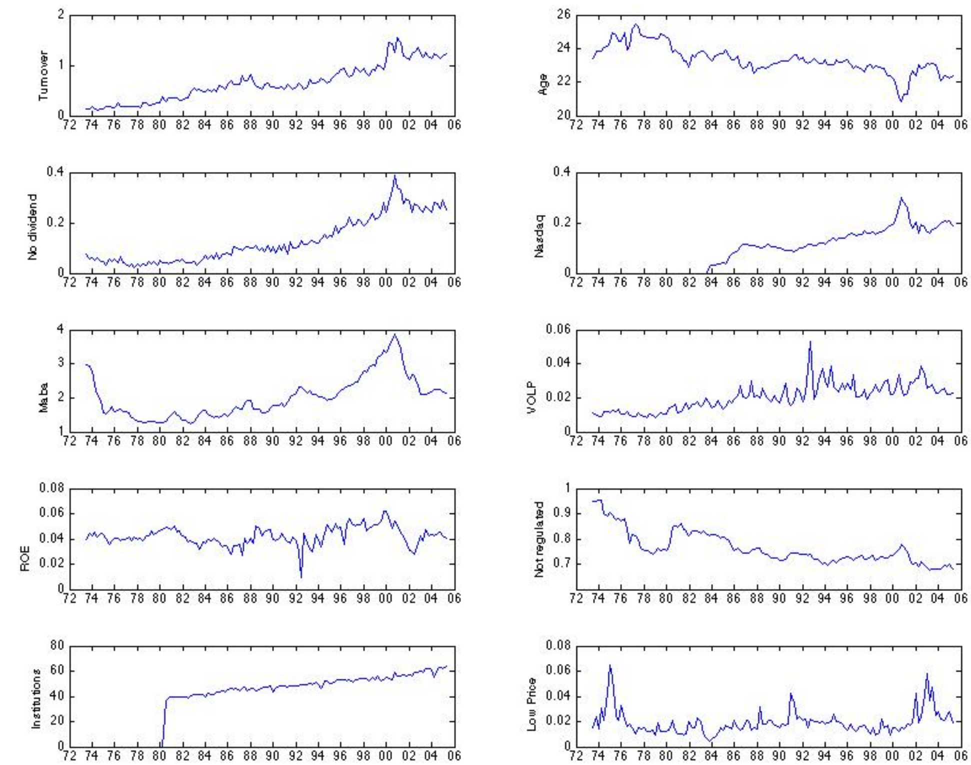

Figure 2: Time-series plot of value-weighted average of the explanatory variables

Table 1
Prior Studies

We summarize the explanation provided in previous studies including the conditioning variables used in cross-sectional and time-series regressions, and the way standard errors are computed for the time-series regressions. ROE is return on equity; VOLP is the time series volatility of ROE (typically based on 12 lags). Bold explanatory variable are proxies for the particular explanation provided in the paper.

	Explanation provided	**Sample period**	**Cross-Sectional Pooled – firm-level analysis**	**Time-Series Market level analysis on average values**	**SE** (for time series analysis)
Campbell et al. (2001)		NYSE, AMEX, Nasdaq firms 1962-1997			
Pastor and Veronesi (2003)	Firm profitability has become more volatile	CRSP/Compustat 1962-2000	**Age, market to book, dividend dummy**, leverage, size, VOLP, ROE.		
Xu and Malikiel (2003)	Earnings Growth	I/B/E/S sample 1986-1995	**Forecasted long term growth,** size		
Xu and Malkiel (2003)	Increased importance of institutions	S&P Firms 1989-1996	**Institutional ownership**, size		
Brandt et al. (2005)	Speculative episodes concentrated in low priced stock	NYSE, AMEX, Nasdaq firms (share code 10, 11) 1962-2004	**Price**, size, market to book, leverage, lagged returns, institutional holdings		
Bennett and Sias (2006)	3 factors - increased value of riskier industries, increased role of small stock firms, measurement error associated within industry concentration		**Ratio of risky industries to safe industries, ratio of number of small companies to large companies, the top weighted average (across industry) of each industry's Herfindahl Index,** time, lagged volatility		
Fink et al. (2006)	The decline in the age of the typical public firm, combined with the increasing number of firms going public.	CRSP/Compustat 1962-2004	**Age**, time, size, market to book, ROA, EPS, leverage, dividend dummy, Exchanges dummy, bubble dummy, crash dummy	**Age**	NA

Wei and Zhang (2006)	Downward trend in profitability, and upward trend in the volatility on profitability	CRSP/Compustat 1976-2000	**ROE, VOLP**, lagged volatility, return, age, size, leverage, market to book	**ROE, VOLP**	NW(3)
Brown and Kapadia (2007)	New listings by riskier firms	CRSP/Compustat (share code 10, 11) 1963-2004	**IPO listing group dummies (pre 1965, 1965-1974, 1975-1984, 1985-1994, 1995-2004),** time, age, size, market to book, dividend dummy, asset tangibility, leverage, turnover	**IPO listing group**	NW(3)
Cao et al. (2007)	An increase in the level and variance of growth options available to managers			**GO, VMABA,** ROE, VOLP	NW(12)
Irvine and Pontiff (2007)	Increased in idiosyncratic volatility in fundamental cash flows which is associated with economy-wide competition	CRSP/Compustat 1962-2003.	**Variance of either (1) EPS, (2) cash flow shock per share, (3) sales shock per share**, ROA, industry turnover, foreign market share	**Variance of either (1) EPS, (2) cash flow shock per share, (3) sales shock per share**	Yule-Walker correction (8)

Table 2
Monte Carlo Study of Spurious Regression

We simulate a series of T observations (125, 250, 500, 1000) from an AR(1) model with autocorrelation coefficient ρ=0.66. We define $X_t = \rho X_{t-1} + \sqrt{1-\rho^2} z_t$, and $Z_t = \rho Z_{t-1} + \sqrt{1-\rho^2} u_t$ is an independent process with the same autocorrelation coefficient, where Z_t and u_t are independent standard normal random variables. We report the rejection frequency of a t-test on the coefficient Z_t in 1) a univariate regression (including intercept) using both OLS and Newey-West standard errors with 3 and 12 lags, and 2) a multivariate regression of Z_t on X_t and the lag of Z_{t-1} using the same three standard error approaches. We repeat this process 1000 times and report the fraction of statistically significant slope coefficients on the irrelevant regressor. In Panels C through F we study the power. We simulate the same AR(1) process for Z_t. The dependent variable is generated $Z_t = X_t + \sqrt{(1-R^2)/R^2} u_t$, which implies a regression of Z_t on X_t will have a coefficient of determination of R^2 and we consider $R^2 = 0.05$ and $R^2 = 0.10$.

Panel A: Univariate Regression				
Sample Size:	0.125	0.250	0.500	0.100
OLS	0.235	0.222	0.223	0.175
NW(3)	0.139	0.108	0.096	0.079
NW(12)	0.127	0.098	0.072	0.058
Panel B: Regression Including Lagged Volatility				
OLS	0.055	0.054	0.046	0.052
NW(3)	0.077	0.060	0.047	0.050
NW(12)	0.100	0.075	0.056	0.053
Panel C: Power Test with Univariate Regression with R2=0.05				
OLS	0.685	0.939	1.000	1.000
NW(3)	0.708	0.943	1.000	1.000
NW(12)	0.732	0.942	1.000	1.000
Panel D: Power Test Regression Including Lagged Volatility with R2=0.05				
OLS	0.679	0.935	1.000	1.000
NW(3)	0.707	0.941	1.000	1.000
NW(12)	0.707	0.941	1.000	1.000
Panel E: Power Test with Univariate Regression with R2=0.10				
OLS	0.927	0.999	1.000	1.000
NW(3)	0.922	0.999	1.000	1.000
NW(12)	0.927	0.999	1.000	1.000
Panel F: Power Test Regression Including Lagged Volatility with R2=0.10				
OLS	0.920	0.999	1.000	1.000
NW(3)	0.921	0.999	1.000	1.000
NW(12)	0.921	0.999	1.000	1.000

Table 3
Cross-Section Distribution - Before and After 1995

The sample includes all American firms traded on NYSE, AMEX and Nasdaq that have no missing observations in a given quarter. The sample has 5995 firms in the period 1973q1-1994q4, and 8986 firms in the period 1995q1-2005q1. Volatility is the volatility calculated as in Campbell et al (2001) based on daily returns. Turnover is the monthly average turnover (number of shares traded divided by number of shares outstanding). Age is the number of years since firm share appears on CRSP. Maba is market to book value of equity as calculated in Cao et al. (2007). VOLP is the variance of quarterly ROEs (Wei and Zhang, 2006). Institution is the combined holdings of all institutional investors. For indicator variables the mean value is provided. The indicator variables are: Nasdaq equals 1 if the firm is traded on Nasdaq; No dividend equals 1 if the firm did not pay dividend during the quarter (*compustat* item 16 is zero); Low price equals 1 if the firm's share price is lower than $10 at the end of the quarter; Not regulated equals 1 if the firm is not classified to an industry whose first SIC code is 4 or 6 (financials and regulated).

Pre-1995

	Mean	Standard deviation	p1	p5	p25	p50	p75	p95	p99
Volatility	0.06	0.24	0.00	0.01	0.02	0.03	0.07	0.20	0.51
Turnover	0.54	0.67	0.03	0.07	0.18	0.34	0.64	1.66	3.39
Age	15.74	9.00	2.16	3.50	7.92	14.35	22.68	30.00	30.00
Maba	1.43	0.89	0.68	0.76	0.97	1.13	1.54	3.06	5.85
VOLP	0.03	0.05	0.00	0.00	0.01	0.01	0.03	0.11	0.30
ROE	0.02	0.07	-0.37	-0.06	0.02	0.03	0.05	0.08	0.16
Institution	22.90	22.65	0.00	0.00	0.00	17.62	40.17	65.04	77.01
Dummy mean	Nasdaq	0.24	No dividend	0.35	Low price	0.27	Not regulated	0.80	

Post-1994

	Mean	Standard deviation	p1	p5	p25	p50	p75	p95	p99
Volatility	0.11	0.25	0.00	0.01	0.02	0.05	0.11	0.37	0.88
Turnover	1.18	1.42	0.05	0.12	0.36	0.71	1.41	3.91	7.64
Age	14.08	9.43	2.08	3.25	5.92	11.09	22.68	30.00	30.00
Maba	1.84	1.32	0.68	0.83	1.06	1.33	2.03	4.96	6.90
VOLP	0.04	0.07	0.00	0.00	0.01	0.02	0.05	0.17	0.37
ROE	0.00	0.11	-0.50	-0.20	-0.00	0.02	0.04	0.09	0.21
Institution	41.64	27.48	0.17	2.13	17.21	40.26	63.89	86.48	98.28
Dummy mean	Nasdaq	0.53	No dividend	0.60	Low price	0.47	Not regulated	0.73	

Table 4
Cross-Section Correlation - Before and After 1995

The sample includes all American firms traded on NYSE, AMEX and Nasdaq that have no missing observations in a given quarter. The sample has 5995 firms in the period 1973q1-1994q4, and 8986 firms in the period 1995q1-2005q1. Under the diagonal the table provides the average (standard deviation) of correlations in a given quarter for the period 1973q1-1994q4; above the diagonal the average (standard deviation) correlation for the period 1995q1-2005q1 is provided. Volatility is the log of the volatility calculated as in Campbell et al (2001) based on daily returns. Turnover is the monthly average turnover (number of shares traded divided by number of shares outstanding). Age is the number of years since firm share appears on CRSP. Maba is market to book value of equity as calculated in Cao et al. (2007). VOLP is the variance of quarterly ROEs (Wei and Zhang, 2006). Inst is the combined holdings of all institutional investors. The indicator variables are: Nasdaq equals 1 if the firm is traded on Nasdaq; No dividend equals 1 if the firm did not pay dividend during the quarter (*compustat* item 16 is zero); Low price equals 1 if the firm's share price is lower than $10 at the end of the quarter; Not regulated equals 1 if the firm is not classified to an industry whose first SIC code is 4 or 6 (financials and regulated).

	Volatility	Turnover	Age	No dividend	Nasdaq	Maba	VOLP	ROE	Not regulated	Inst	Low price
Volatility		0.3562	-0.3357	0.5856	0.4661	0.1596	0.3564	-0.3682	0.3913	-0.2765	0.5437
		(0.079)	(0.072)	(0.029)	(0.073)	(0.079)	(0.031)	(0.040)	(0.036)	(0.076)	(0.054)
Turnover	0.3008		-0.1734	0.2722	0.2231	0.3107	0.1185	-0.069	0.2129	0.2531	-0.0797
	(0.083)		(0.058)	(0.056)	(0.089)	(0.065)	(0.058)	(0.052)	(0.027)	(0.119)	(0.073)
Age	-0.3737	-0.1193		-0.3906	-0.3938	-0.0994	-0.1209	0.1667	-0.0151	0.1759	-0.2184
	(0.081)	(0.077)		(0.054)	(0.035)	(0.058)	(0.020)	(0.016)	(0.033)	(0.025)	(0.029)
No	0.5186	0.1809	-0.3126		0.3761	0.1666	0.2534	-0.2543	0.3870	-0.1434	0.4364
dividend	(0.073)	(0.075)	(0.115)		(0.037)	(0.044)	(0.018)	(0.016)	(0.042)	(0.068)	(0.035)
Nasdaq	0.3220	0.2386	-0.4511	0.2699		0.1324	0.1085	-0.1721	0.1134	-0.2812	0.2627
	(0.215)	(0.074)	(0.114)	(0.134)		(0.048)	(0.027)	(0.025)	(0.035)	(0.035)	(0.024)
Maba	0.0039	0.1427	-0.1153	0.0190	0.1111		0.1171	-0.0378	0.2345	0.0748	-0.1038
	(0.099)	(0.076)	(0.065)	(0.072)	(0.055)		(0.052)	(0.052)	(0.030)	(0.051)	(0.074)
VOLP	0.2935	0.0759	-0.078	0.2603	0.0224	-0.0005		-0.3305	0.1589	-0.1646	0.3070
	(0.051)	(0.044)	(0.039)	(0.043)	(0.045)	(0.041)		(0.055)	(0.030)	(0.033)	(0.038)
ROE	-0.1867	0.0273	0.0272	-0.1429	-0.0501	0.2055	-0.1474		-0.1278	0.1916	-0.3357
	(0.124)	(0.066)	(0.069)	(0.908)	(0.052)	(0.089)	(0.232)		(0.031)	(0.032)	(0.041)
Not	0.2475	0.0908	-0.0010	0.1515	0.0446	0.1138	0.0398	-0.0507		0.1003	0.2179
regulated	(0.078)	(0.061)	(0.053)	(0.083)	(0.110)	(0.048)	(0.035)	(0.043)		(0.045)	(0.040)
Inst	-0.3421	0.1732	0.2866	-0.2987	-0.1771	0.0499	0.1722	0.1322	0.1017		-0.4728
	(0.065)	(0.093)	(0.047)	(0.033)	(0.103)	(0.041)	(0.027)	(0.048)	(0.041)		(0.044)
Low price	0.5352	-0.0580	-0.2722	0.4672	0.1783	-0.1737	0.2627	-0.2254	0.1158	-0.4390	
	(0.098)	(0.040)	(0.075)	(0.056)	(0.106)	(0.074)	(0.053)	(0.077)	(0.043)	(0.060)	

Table 5
The Cross-Section Determinants of Volatility – Before and After 1995

The sample has 5995 firms in the period 1973q1-1994q4, and 8968 firms in the period 1995q1-2005q1. The table provides cross sectional regression for the different periods using (a) firm and quarter fixed-effects, and (b) double clustered stand errors as in Petersen (2007). Volatility is the log of the volatility calculated as in Campbell et al (2001) based on daily returns. Turnover is the monthly average turnover (number of shares traded divided by number of shares outstanding). Size is the log of the market value of the firm's common shares. Age is the number of years since firm share appears on CRSP. Maba is market to book value of equity as calculated in Cao et al. (2007). VOLP is the variance of quarterly ROEs (Wei and Zhang, 2006). Institution is the combined holdings of all institutional investors. The indicator variables are: Nasdaq equals 1 if the firm is traded on Nasdaq; No dividend equals 1 if the firm did not pay dividend during the quarter (*compustat* item 16 is zero); Low price equals 1 if the firm's share price is lower than $10 at the end of the quarter; Not regulated equals 1 if the firm is not classified to an industry whose first SIC code is 4 or 6 (financials and regulated).All variables are normalized and *t*-statistic of coefficient is provided in parenthesis.

	1973q1 – 1994q4		1995q1-2005q1		1973q1-2005q1	
Dependent	Volatility		Volatility		Volatility	
	1(a)	1(b)	2(a)	2(b)	3(a)	3(b)
Lag volatility	0.36284	0.60431	0.31426	0.62401	0.39897	0.61721
	(145.59)	(23.09)	(113.73)	(36.01)	(208.46)	(40.80)
Size	-0.11217	-0.06169	-0.18721	-0.05369	-0.11889	-0.05584
	(-18.76)	(-4.82)	(-29.34)	(-5.06)	(-28.97)	(-4.73)
Turnover	0.16368	0.19474	0.23362	0.12402	0.20172	0.13552
	(79.53)	(10.51)	(108.56)	(17.53)	(129.63)	(17.38)
Age	-0.03087	-0.03877	-0.10792	-0.01375	-0.06465	-0.02591
	(-4.91)	(-8.17)	(-7.01)	(-3.07)	(-16.25)	(-6.89)
No dividend	0.03041	0.04214	0.02565	0.04604	0.03257	0.04603
	(11.42)	(7.88)	(7.03)	(8.63)	(14.98)	(11.53)
Nasdaq	0.00920	0.01701	0.026186	0.03663	0.03088	0.02963
	(1.63)	(1.65)	(4.48)	(5.61)	(8.56)	(4.85)
Maba	-0.00882	0.00908	-0.00939	0.00739	-0.00920	0.00736
	(-3.31)	(1.24)	(-3.56)	(1.16)	(-5.00)	(1.30)
VOLP	0.03256	0.02134	0.02195	0.02130	0.02393	0.02088
	(13.11)	(4.72)	(12.60)	(5.05)	(19.37)	(6.49)
ROE	-0.04053	-0.05105	-0.04668	-0.03894	-0.04563	-0.04057
	(-24.63)	(-10.19)	(-24.98)	(-8.69)	(-35.09)	(-11.08)
Not regulated	-0.00529	0.05580	0.01356	0.06038	0.02384	0.05862
	(-0.56)	(8.97)	(1.72)	(9.50)	(4.44)	(9.25)
Institutions	-0.00630	-0.05385	-0.02686	-0.04560	-0.02355	-0.04775
	(-1.94)	(-2.58)	(-6.68)	(-4.16)	(-9.13)	(-3.53)
Low price	0.09975	0.11910	0.07800	0.09913	0.09879	0.10813
	(44.41)	(17.64)	(30.44)	(12.31)	(57.92)	(19.65)
Number of observations	119,344	119,344	127,263	127,263	246,607	246,607
R squared	0.7335	0.6902	0.7132	0.7237	0.7485	0.7186

Table 6
Summary Statistics of Value-Weighted Averaged Time-Series Variables

Descriptive statistics of the value-weighted volatility and value-weighted averages of the ten conditioning variables. Panel A reports the mean and standard deviation for the full sample, the sub period 1973q1-1994q4, and the sub period 1995q1-2005q1respectively. Panel B provides correlation matrix of the full sample of value-weighted variables. Firm-level variables used to derive value-weighted variables are: volatility is calculated as in Campbell et al (2001) based on daily returns. Turnover is the monthly average turnover (number of shares traded divided by number of shares outstanding). Age is the number of years since firm share appears on CRSP. Maba is market to book value of equity as calculated in Cao et al. (2007). VOLP is the variance of quarterly ROEs (Wei and Zhang, 2006). Institution is the combined holdings of all institutional investors. The indicator variables are: Nasdaq equals 1 if the firm is traded on Nasdaq; No dividend equals 1 if the firm did not pay dividend during the quarter (*compustat* item 16 is zero); Low price equals 1 if the firm's share price is lower than $10 at the end of the quarter; Not regulated equals 1 if the firm is not classified to an industry whose first SIC code is 4 or 6 (financials and regulated).

Panel A

	Volatility	Turnover	Age	No dividend	Nasdaq	Maba	VOLP	ROE	Not regulated	Institution	Low price
Mean	0.0288	0.6447	23.3392	0.1277	0.0923	2.0048	0.0203	0.0422	0.7643	38.7403	0.0193
SD	0.0200	0.3603	0.8381	0.0895	0.0782	0.6168	0.0079	0.0074	0.0644	21.3886	0.0098
Mean (Pre-1995)	0.0234	0.4417	23.6950	0.0730	0.0498	1.7005	0.0177	0.0400	0.7869	30.5901	0.0186
SD (Pre-1995)	0.0139	0.2018	0.6847	0.0335	0.0518	0.3705	0.0078	0.0061	0.0649	21.4382	0.0093
Mean (Post 1994)	0.0401	1.0754	22.5841	0.2439	0.1826	2.6504	0.0259	0.0468	0.7164	56.0346	0.0206
SD (Post 1994)	0.0257	0.2117	0.6022	0.0519	0.0373	0.5332	0.0044	0.0079	0.0249	3.6477	0.0107

Panel B

Turnover	0.5094									
Age	-0.4883	-0.8361								
No dividend	0.4964	0.934	-0.8173							
Nasdaq	0.4388	0.9408	-0.8705	0.9459						
Maba	0.6046	0.6866	-0.7122	0.8168	0.7656					
VOLP	0.2425	0.6908	-0.6495	0.6500	0.7357	0.5100				
ROE	0.2384	0.1885	-0.2322	0.3121	0.2521	0.3679	-0.0104			
Not regulated	-0.0048	-0.6886	0.4872	-0.6042	-0.7179	-0.2434	-0.6362	-0.0595		
Institutions	0.2390	0.8175	-0.8214	0.6892	0.7928	0.4423	0.7427	0.0932	-0.6706	
Low price	0.1129	0.1062	0.0213	0.1423	0.0998	0.0077	0.0883	-0.1111	0.0027	0.0015

Table 7
The Time-Series Determinants of Value-Weighted Average Volatility – Full Sample Results

The sample has 128 observations in the period 1973q1-2005q1. The dependent variable is value-weighted volatility. All variables are defined in Table 6. Each column contains a different specification of the regression model. For each regression the adjusted R-squared is reported along with the Durbin-Watson statistic (DW) to assess the problem of serial correlation. The table reports the point estimate and Newey-West *t*-statistics computed using 3 lags.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Intercept	0.0105	0.3011	0.0146	0.0184	-0.0106	0.0163	0.0016	0.0299	0.0201	0.0243	0.1862
	(1.84)	(3.08)	(3.69)	(5.44)	(-1.25)	(3.16)	(0.11)	(1.53)	(5.53)	(4.38)	(2.22)
Turnover	0.0283										0.1035
	(2.70)										(5.59)
Age		-0.0117									-0.0115
		(-2.83)									(-3.37)
No dividend			0.1110								-0.2513
			(2.86)								(-2.98)
Nasdaq				0.1123							-0.1391
				(2.45)							(-1.99)
Maba					0.0196						0.0179
					(4.32)						(2.66)
VOLP						0.6136					0.2996
						(1.98)					(1.57)
ROE							0.6452				0.4151
							(1.79)				(2.71)
Not regulated								-0.0015			0.0631
								(-0.06)			(1.87)
Institution									0.0002		-0.0006
									(1.98)		(-3.66)
Low price										0.231	0.2912
										(1.21)	(2.05)
Adj. R squared	0.2536	0.2324	0.2405	0.1861	0.3605	0.0513	0.0494	-0.0079	0.0496	0.0049	0.6062
DW	0.8757	1.0606	1.0332	0.9427	1.1713	0.8417	0.8379	0.7612	0.8156	0.7900	1.5361

Table 8
The Time-Series Determinants of Value-Weighted Average Volatility – Full Sample Results

The sample has 128 observations in the period 1973q1-2005q1. The dependent variable is value-weighted volatility. All variables are defined in Table 6. Each column contains a different specification of the regression model. For each regression the adjusted R-squared is reported along with the Durbin-Watson statistic (DW) to assess the problem of serial correlation. The table reports the point estimate and OLS *t*-statistics.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	0.0109	0.0045	0.1482	0.0076	0.0087	-0.0077	0.0072	-0.0039	0.0096	0.0086	0.0129	0.1302
	(4.45)	(1.57)	(3.31)	(2.91)	(3.44)	(-1.74)	(1.81)	(-0.48)	(0.57)	(2.66)	(3.83)	(1.17)
Lag volatility	0.6192	0.4878	0.4997	0.4944	0.5284	0.4103	0.5968	0.5958	0.6193	0.5976	0.6361	0.2367
	(8.84)	(6.49)	(6.39)	(6.25)	(6.92)	(5.31)	(8.22)	(8.46)	(8.80)	(8.24)	(8.72)	(3.15)
Turnover		0.0158										0.0956
		(3.79)										(7.54)
Age			-0.0057									-0.0085
			(-3.07)									(-2.19)
No dividend				0.0543								-0.2510
				(3.07)								(-4.50)
Nasdaq					0.0524							-0.1160
					(2.68)							(-1.48)
Maba						0.0123						0.0162
						(4.91)						(3.42)
VOLP							0.2134					0.2618
							(1.16)					(1.08)
ROE								0.3677				0.3981
								(1.93)				(2.33)
Not regulated									0.0017			0.0452
									(0.08)			(1.09)
Institution										0.0001		-0.0006
										(1.13)		(-4.08)
Low price											-0.1258	0.1671
											(-0.84)	(1.25)
Adj. R squared	0.3777	0.4374	0.4168	0.4168	0.4069	0.4741	0.3794	0.3909	0.3728	0.3791	0.3763	0.6340
DW	2.227	2.022	2.1643	2.1148	2.1457	2.0913	2.2025	2.2236	2.2276	2.2054	2.2373	2.0442

Table 9
The Time-Series Determinants of Value-Weighted Average Volatility – Allowing for Break after 1994

The sample has 128 observations in the period 1973q1-2005q1. The dependent variable is value-weighted volatility. All variables are defined in Table 6. Models are collected in pairs of column: the first column reports the parameter estimate and *t-statistic* in the 1974-1994 period, and the second column is the *difference* between the pre-1995 and post-1994 periods. For each model we compute initially a model without accounting for lagged values of volatility (and compute the standard errors using Newey-West with 3 lags) and then with lagged volatility as a conditioning variable.

	(1)		(2)		(3)		(4)		(5)		(6)	
Intercept	0.0193	-0.062	0.0139	-0.0409	0.0233	-0.0651	0.0175	-0.0356	0.1205	-0.4941	0.1261	-0.5137
	(3.19)	(-2.44)	(3.12)	(-3.17)	(9.66)	(-5.21)	(5.08)	(-2.69)	(1.71)	(-2.77)	(1.05)	(-1.54)
Lag volatility			0.242	0.3199							-0.0358	0.1085
			(2.17)	(2.10)							(-0.34)	(0.63)
Turnover	0.0094	0.0677	0.0086	0.0327					0.1145	-0.0112	0.1156	-0.012
	(0.68)	(2.32)	(1.12)	(2.22)					(2.25)	(-0.21)	(5.68)	(-0.44)
Age									-0.0076	0.0105	-0.0079	0.012
									(-2.48)	(1.29)	(-1.87)	(0.81)
No dividend									0.0139	-0.0102	0.016	-0.02
									(0.22)	(-0.10)	(0.13)	(-0.12)
Nasdaq									-0.3228	0.0992	-0.3282	0.1247
									(-3.74)	(0.51)	(-2.96)	(0.35)
Maba					0.0017	0.4472	0.0012	0.1961	0.0092	0.0129	0.009	0.0109
					(0.048)	(5.15)	(0.04)	(2.20)	(1.94)	(1.75)	(1.47)	(0.98)
VOLP									0.1047	-0.1237	0.1107	-0.1335
									(0.84)	(-0.37)	(0.41)	(-0.23)
ROE									0.3891	-0.3437	0.3865	-0.2922
									(1.35)	(-0.80)	(1.80)	(-0.68)
Not regulated									0.0256	0.4033	0.0275	0.3784
									(1.09)	(2.96)	(0.59)	(1.71)
Institution									-0.0005	-0.0013	-0.0005	-0.0012
									(-1.68)	(-1.39)	(-3.01)	(-1.06)
Low price									0.5396	-0.0196	0.57	-0.14
									(5.20)	(-0.10)	(3.16)	(-0.39)
Adj. R squared	0.3533		0.4856		0.3581		0.4596		0.703		0.6984	
DW	0.9428		1.8413		1.2729		2.034		2.1137		2.0898	