The Time-Series Behavior and Pricing of Idiosyncratic Volatility: Evidence from 1926 to 1962

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Abstract

The recent literature on idiosyncratic volatility has documented three main empirical findings. First, Campbell, Lettau, Malkiel, and Xu (2001) show that idiosyncratic volatility exhibits an upward trend between 1962 and 1997. Second, Goyal and Santa-Clara (2003) find that aggregate measures of idiosyncratic volatility predict one-month-ahead excess market returns from 1962 to 1999. Third, Ang, Hodrick, Xing, and Zhang (2006a) report a negative and significant relation between idiosyncratic volatility and cross-sectional stock returns from 1963 to 2000. The first result has led to a number of papers attempting to explain the causes of this upward trend, while the second and third results remain highly controversial. We re-examine these three findings using a 37-year holdout sample of daily returns from 1926 to 1962. We find robust empirical evidence of (1) a statistically significant *downward* trend in idiosyncratic volatility, (2) an *insignificant* relation between average idiosyncratic volatility and one-month-ahead excess market returns, and (3) a *highly significant* inverse relation between idiosyncratic volatility and cross-sectional stock returns. These results shed new light on the time-series behavior and pricing of idiosyncratic volatility.

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I. Introduction

Idiosyncratic volatility has received considerable attention from academic researchers over the past several years. We use a 37-year holdout sample to re-examine the three most prominent, if controversial, findings related to the time series behavior and pricing of idiosyncratic volatility. First, Campbell, Lettau, Malkiel, and Xu's (CLMX) (2001) find that the level of idiosyncratic volatility has increased steadily from 1962 to 1997. Second, Goyal and Santa-Clara (2003) show that average idiosyncratic volatility has predictive ability for one-month-ahead excess market returns from 1962 to 1999, although this finding is refuted by Bali, Cakici, Yan, and Zhang (BCYZ) (2005). Third, and perhaps most perplexing, Ang, Hodrick, Xing, and Zhang (AHXZ) (2006a) find a significantly negative relation between idiosyncratic risk and cross-sectional stock returns from 1963 to 2000. This result represents a "substantive puzzle" for asset pricing theory and contradicts previous findings of Lintner (1965) and Lehmann (1990).

All previous idiosyncratic volatility studies use daily data only in the post-1962 period because of the lack of pre-1962 CRSP daily data.[1] More recently, CRSP has extended its daily data file to include an additional 37-year period beginning in 1926. This is a substantial extension that almost doubles the previous sample period. It also includes significant economic events such as the Great Depression, World War II, and the beginning of the Bretton Woods monetary system, as well as several episodes of expansion and contraction in the real economy.

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[1]Few idiosyncratic volatility studies include any results before 1962, and the ones that include pre-1962 results use monthly data. It is well-known from Merton (1980) and Andersen, Bollerslev, Diebold, and Labys (2003) that return volatility can be more precisely estimated from daily data than from monthly data.

This additional database allows researchers to test the degree to which previous empirical results are subject to overfitting or data-snooping. As stated in Campbell, Lo, and MacKinlay (1997, p. 524), "Careful out-of-sample performance evaluation can uncover overfitting problems, and if relatively few out-of-sample tests are conducted, or if they are conducted over different (and weakly correlated) datasets, this will minimize the effects of data-snooping."[2]

Using this new CRSP database of daily stock returns for 1926-1962, we re-examine the time trend, forecasting ability, and cross-sectional risk premium (discount) associated with idiosyncratic volatility. To the best of our knowledge, this is the first study to investigate the patterns and pricing of idiosyncratic volatility based on daily data from the pre-1962 period. Our empirical analysis generates several new results.

First, we document a significantly negative trend for idiosyncratic volatility between 1926 and 1962. This downward trend contrasts sharply with the upward trend identified in the post-1962 period. We further show that the negative trend is a pervasive phenomenon during our 37-year period; it is robust to the inclusion of Depression and World War II dummy variables, equal- versus value weightings, and the use of Vogelsang's (1998) trend test. One contribution of this finding is that it will provide a useful testing ground for hypotheses regarding the underlying sources of the post-1962 upward trend. If declining firm age (Fink, Fink, Grullon, and Weston (2006)) or rising product market competition (Irvine and Pontiff (2005)) caused the post-1962 increase in idiosyncratic volatility, for example, then rising firm age or declining product market competition should be found in the pre-1962 period.

Second, we do not find any evidence that average idiosyncratic volatility forecasts excess market returns during 1926-1962. This result casts serious doubt on the stability of the

[2]See Lo and MacKinley (1990) for additional evidence on data-snooping and its misleading effects on statistical inference.

relationship documented by Goyal and Santa-Clara (2003). While BCYZ (2005) and Wei and Zhang (2005) show that the idiosyncratic risk-return relation is not robust to the inclusion of more recent years, we find that the relation does not hold at all during a 37-year period prior to 1962.[3] While Goyal and Santa-Clara (2003) find a significant relationship between excess market returns and equal-weighted volatility for 1962-1999 and BCYZ (2005) show that this relationship disappears for value-weighted idiosyncratic volatility, we find no significant relationship between excess market returns and average idiosyncratic volatility using either weighting scheme prior to 1962. Overall, our results show that idiosyncratic volatility does not forecast excess market returns between 1926 and 1962.

Unlike the time-series relation between idiosyncratic volatility and excess market returns, our third finding strongly confirms the inverse relation between idiosyncratic volatility and cross-sectional stock returns documented in AHXZ (2006a). We examine the performance of idiosyncratic volatility-sorted portfolios with respect to the CAPM, Fama-French (1993, 1996), and Carhart (1997) models. Our results confirm that firms with high idiosyncratic volatility are consistent underperformers, while firms with low idiosyncratic volatility earn positive excess returns. The difference in alphas between the extreme quintile portfolios sorted on idiosyncratic volatility is 0.60% - 0.84% per month. These results are robust to additional sorting on several control variables including size, turnover, share price, percent of zero returns, Amihud's (2002) illiquidity measure, and lagged six-month returns. Finally, we find a negative and significant relation between idiosyncratic volatility and stock returns using a cross-sectional regression framework. This negative relation remains significant after controlling for other firm

[3] Although Goyal and Santa-Clara (2003) and BCXZ (2005) perform some testing from the pre-1962 period, both studies use "low-frequency" monthly returns. Goyal and Santa-Clara (2003) find that idiosyncratic volatility predicts future market returns for the longer, low-frequency sample, and BCXZ (2005) show that this result is not robust.

characteristics that are related to the cross-section of stock returns. We conclude that AHXZ's (2006a) substantive puzzle was alive and well in the pre-1962 period.

Overall, our results shed additional light on the time-series properties and pricing of idiosyncratic volatility. The negative time trend in idiosyncratic volatility during 1926-1962 provides a unique setting in which to test competing hypotheses about the underlying causes of idiosyncratic volatility. The inability of average idiosyncratic volatility to predict excess market returns during our 37-year period suggests that previous evidence of predictability is unstable at best. Finally, our confirmation of a negative relation between idiosyncratic volatility and cross-sectional stock returns demonstrates that AHXZ's (2006a) puzzling results are not caused by data-snooping or overfitting. This finding highlights the need for additional research into the underlying causes of this inverse relationship.

In the next section, we review the relevant literature on idiosyncratic volatility. In section III, we describe our data and provide variable definitions. In section IV, we present and discuss our empirical findings. In section V, we summarize and conclude our study.

II. Related Research

We divide our literature review into the three main areas related to our empirical analysis. In the first section, we review the evidence on time trends in idiosyncratic volatility. In the second section, we discuss the controversy over the relation between average idiosyncratic volatility and future market returns. In the third section, we review the evidence on the relation between idiosyncratic volatility and cross-sectional stock returns.

A. Time Trends

CLMX (2001) investigate the time-series behavior of market-, industry-, and firm-level volatilities from 1962 to 1997. They find that while market- and industry-level volatilities are relatively stable over this time period, firm-level volatility more than doubles.[4] Summarizing their empirical findings, CLMX (2001) comment that (p. 41) "A fascinating area for future research will be to explain the behavior of our disaggregated volatility measures, and particularly the observed upward trend in idiosyncratic volatility." This challenge to identify the underlying cause(s) of the upward trend in idiosyncratic volatility has generated a small cottage industry.

Xu and Malkiel (2003) investigate whether the rise in institutional ownership explains the upward trend in idiosyncratic volatility. They show that institutional ownership Granger causes idiosyncratic volatility (but not vice versa), a result consistent with Denis and Strickland (2005) and Bennett, Sias, and Starks (2003). Irvine and Pontiff (2005) hypothesize that the upward trend in idiosyncratic volatility is due to increasing competitiveness in the product market. Fink, Fink, Grullon, and Weston (2006) show that the higher proportion of young firms traded in the capital markets explains the positive trend in idiosyncratic risk. They show that the age of a typical firm that issues public equity has decreased from almost 40 years in the 1960s to less than five years in the late 1990s.[5] In a subtly different argument, Brown and Kapadia (2006) claim that it is not the reduction in firm age, per se, that leads to higher idiosyncratic volatility. Instead, rising idiosyncratic volatility is attributable to a change in the fundamental characteristics of the typical firm.[6] Brown and Kapadia (2006) argue that greater financial market development, as described in Rajan and Zingales (2003), has enabled riskier firms to gain

[4] Morck, Yeung, and Yu (2000) find a similar upward trend in the US market, and Li, Morck, Yang, and Yeung (2004) confirm the same pattern, albeit weaker, in emerging markets.

[5] This "IPO vintage" argument is broadly consistent with a number of other studies (Pastor and Veronesi (2003), Fama and French (2004), Cao, Simin, and Zhao (2005), Bennett and Sias (2004), Dennis and Strickland (2005), and Wei and Zhang (2006)) since younger firms are also smaller, less profitable, more volatile, and tend to operate in a single industry.

[6] In a related finding, Rajgopal and Venkatachalam (2005) show that earnings quality has deteriorated since 1960, even after controlling for youthful new listings.

access to the public markets. In contrast, Brandt, Brav, and Graham (2005) argue that investor irrationality is responsible for the upward trend in idiosyncratic volatility.

In summary, previous research has documented an increase in idiosyncratic volatility from 1962 to 1997. Numerous studies have confirmed this upward trend and attempted to explain its underlying causes. Potential explanations based on firm characteristics include changes in the average firm's age, size, growth opportunities, fundamental riskiness, as well as the level, quality, and variability of corporate earnings. Possible institutional or environmental explanations include changes in institutional ownership, product market competition, and capital market sophistication.

B. Predicting Market Returns

Merton's (1973) intertemporal capital asset pricing model (ICAPM) suggests that there is a positive relation between expected returns and aggregate stock market risk.[7] In contrast to the relation between market returns and market risk, Goyal and Santa-Clara (2003) examine the relation between market returns and idiosyncratic risk between 1962 and 1999. They find that average stock return variance (largely idiosyncratic) has significant forecasting ability with respect to one-month-ahead excess market returns, while market volatility has no such forecasting ability. Bali, Cakici, Yan, and Zhang (BCYZ) (2005) argue that the relation between market returns and idiosyncratic volatility is tenuous at best. BCYZ show that Goyal and Santa-Clara's (2003) results are driven by small firms traded on Nasdaq, are more consistent with a liquidity premium than an idiosyncratic risk premium, disappear in an updated sample, and do not hold for value-weighted volatility measures.

[7] Previous studies have yielded mixed results with some studies finding a positive and significant relation (Ghysels, Santa-Clara, and Valkanov (2005)), a negative and significant relation (Campbell (1987)), a mostly insignificant relation (Baillie and DeGennaro (1990)), and a positive or negative relation that depends on the method of analysis (Harvey (2001)). In addition, French, Schwert, and Stambaugh (1987) find a significant negative relation between market excess returns and unexpected market volatility.

Although subsequent studies have not resolved this controversy, they have added new evidence to the puzzle. Wei and Zhang (2005) examine an extended sample of monthly returns and find no predictability between idiosyncratic risk and future market returns. Guo and Savickas (2006) find that idiosyncratic volatility is *negatively* related to future market returns after controlling for market volatility. Brown and Ferreira (2005) show that small-firm idiosyncratic volatility can predict future excess returns on size and age portfolios, as well as on the market portfolio. Jiang and Lee (2006) argue that because volatility is persistent through time, a single lagged volatility variable might not capture the dynamic relation between volatility and excess market returns. After accounting for serial correlations, Jiang and Lee (2006) find a positive and significant relation between idiosyncratic volatility and market returns, although the effects are often delayed.

In summary, there is considerable controversy about the ability of idiosyncratic volatility to forecast future market returns. Previous results have proven to be sensitive to model specifications, time periods, and return intervals.

C. Cross-Sectional Stock Returns

In addition to analyzing idiosyncratic volatility and aggregate market returns, previous studies have examined the relation between idiosyncratic volatility and the cross-section of expected stock returns. Financial theory suggests that investors require a positive risk premium if they are unable to avoid idiosyncratic risk through diversification.[8] Consistent with theory, early studies (e.g., Lintner (1965) and Lehmann (1990)) generally find a positive relation between idiosyncratic volatility and expected stock returns. Recent evidence by Ang, Hodrick, Xing, and Zhang (AHXZ) (2006a), in contrast, find a negative and significant relation between

[8] Investors might remain less-than-fully diversified because of information or transaction costs (Merton (1987), Malkiel and Xu (2002), Jones and Rhodes-Kropf (2003)).

idiosyncratic risk and returns from 1963 to 2000. AHXZ explain that (p. 261) "The difference between our results and the results of past studies is that the past literature either does not examine idiosyncratic volatility at the firm level or does not directly sort stocks into portfolios ranked on this measure of interest." AHXZ's finding of a negative and significant relation, though counterintuitive, is robust to controlling for various firm characteristics (e.g., size, value, volume, liquidity, momentum, analyst forecast dispersion) and market conditions (e.g., bull and bear markets, recessions and expansions, high and low market volatility).

Fu (2005) employs an exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model to estimate time-varying idiosyncratic volatility from monthly stock returns. His empirical results indicate a positive relation between expected returns and conditional or expected idiosyncratic volatility. Spiegel and Wang (2005) also find a positive relation between idiosyncratic volatility and stock returns during 1962-2003 based on monthly data. Ang, Hodrick, Xing, and Zhang (AHXZ) (2006b), however, confirm their U.S. finding of a negative relation between idiosyncratic volatility and stock returns for 23 developed markets around the world.

In summary, there is substantial controversy regarding the relationship between idiosyncratic volatility and the cross-section of expected returns. Previous results are sensitive to both model specification and return intervals. Our 37-year sample period of daily returns will add considerable weight to the existing evidence.

III. Data, Variables, and Descriptive Statistics

In this section, we first discuss our data and sample. We then describe our variable constructions. In the final subsection, we present descriptive statistics.

A. Data and Sample

Our sample period is from January 1926 to June 1962. We obtain daily stock returns, share prices, number of shares outstanding, and trading volume from the CRSP database. We obtain monthly Fama and French (1993, 1996) factors as well as the momentum factor from Kenneth French's website.[9] We obtain three-month Treasury bill rates, 10-year Treasury bond yields, and Moody's Baa corporate bond yields from the Federal Reserve Bank of St. Louis's website.[10] We calculate term spread (TERM) as the difference between the 10-year Treasury bond yield and the 3-month Treasury bill rate. We calculate default spread (DEFAULT) as the difference between Moody's Baa corporate bond yield and the10-year Treasury bond yield. Relative short rate (RREL) is defined as the current three-month T-bill rate minus its 12-month moving average. We obtain monthly dividend yields (DP) for the S&P 500 index from Amit Goyal's website.[11]

B. Measures of Idiosyncratic Volatility

1. Firm-level Idiosyncratic Volatility

For each stock in each month, we estimate the following regression model using daily returns:

$$r_t - r_{f,t} = \alpha + \beta\left(r_{m,t} - r_{f,t}\right) + \varepsilon_t \qquad (1)$$

where r_t is the stock return, $r_{f,,t}$ is the risk-free return, and $r_{m,t}$ is the value-weighted market return. We define idiosyncratic volatility as $ivol = \sqrt{Var(\varepsilon_t)}$. We define total volatility as the standard deviation of daily stock returns $totvol = \sqrt{Var(r_t)}$.

2. Average Idiosyncratic Volatility

[9] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/
[10] http://research.stlouisfed.org/fred2/
[11] http://www.bus.emory.edu/AGoyal/

Based on our firm-level idiosyncratic volatility, we construct four average idiosyncratic volatility measures as follows:

IVOL^{EW}: The equal-weighted average *ivol* across all firms.

IVOL^{VW}: The market capitalization-weighted average *ivol* across all firms.

$\text{TOTVOL}^{\text{EW}}$: The equal-weighted average *totvol* across all firms.

$\text{TOTVOL}^{\text{VW}}$: The market capitalization-weighted average *totvol* across all firms.

In Figure 1, we graph the equal-weighted and value-weighted average idiosyncratic volatility from 1926 to 1962. Both data series show a brief increase from 1926 until around 1933, followed by a steady decline from 1933 until approximately 1953. We find the same general patterns for the equal-weighted and value-weighted average total volatility in Figure 2. Although there are substantial variations over time, we find an overall downward trend in the average idiosyncratic volatility.

C. Descriptive Statistics

We report descriptive statistics for the average idiosyncratic volatility and macroeconomic variables in Table 1. Panel A includes the mean, median, standard deviation, maximum, minimum, and first-order serial correlation for our variables. The equal-weighted volatility measures (IVOL^{EW} and $\text{TOTVOL}^{\text{EW}}$) have higher mean and median values relative to their value-weighted counterparts (IVOL^{VW} and $\text{TOTVOL}^{\text{VW}}$). The equal-weighted measures also have wider ranges between minimum and maximum values, as well as larger standard deviations. The equal-weighted idiosyncratic volatility mean and median values, for example, are 2.48% and 1.95% respectively, while their value-weighted counterparts are 1.27% and 1.13%. The minimum and maximum equal-weighted idiosyncratic volatilities range from 1.15% to 9.15%, while the value-weighted extremes only vary from 0.72% to 4.39%. These results are consistent with previous results showing that smaller firms tend to have higher levels of idiosyncratic volatility. We also note that equal-weighted volatilities are slightly more persistent than value-weighted volatilities, as evidenced by their higher serial correlations.

The mean (median) excess market return (MKTRF) over our sample period is 0.82% (1.34%) per month. The minimum monthly excess return is -29.03% and the maximum monthly return is 38.18%. Our mean (median) dividend yield (DP) is 5.12% (4.87%) on an annualized basis. The average term spread between 10-year Treasury bonds and 3-month Treasury bills (TERM) is 1.52% per month. The average default spread between Moody's Baa corporate bonds and 10-year Treasury bonds (DEFAULT) is 1.88% per month. Median values for term and default spreads are similar to their respective mean values. Our mean and median relative short rates (RREL), reflecting the difference between 3-month Treasury bill rates and their 12-month moving averages, are both very close to zero. All variables with the exception of excess market returns have relatively high serial correlations.

In Panel B, we report correlations among the average idiosyncratic volatility measures, and in Panel C, we provide correlations between average idiosyncratic volatility and macroeconomic variables. As seen in Panel B, our average volatility measures are all highly correlated with each other. The highest correlation (0.99) is between equal-weighted idiosyncratic and total volatility. The lowest correlation (0.88) is between equal-weighted idiosyncratic volatility and value-weighted total volatility.

In Panel C, we find consistently negative (if small) correlations between excess market returns and all four measures of average volatility. The strongest correlation (-0.16) is between value-weighted total volatility and excess returns. When volatility is high, excess market returns tend to be low. Similar to these excess return correlations, we also find consistently negative correlations between relative short rates and all four measures of volatility. When the current short rate is above its moving average, volatility is relatively low. Our remaining variables have consistently positive correlations with volatility. When the term structure is steep (i.e., long-term rates exceed short-term rates) or the default premium is large, volatility is high. The relation between equal-weighted volatility and default premiums are particularly strong, with a correlation of 0.93 for idiosyncratic volatility and 0.90 for total volatility. Our Panel C results also show a consistently positive relation between volatility and dividend yields. In summary, volatility is negatively related to returns and short-term rates, and positively related to term spreads, default spreads, and dividend yields.

IV. Empirical Results

We divide our empirical results into three sections. In the first section, we report our empirical evidence on the time trend in idiosyncratic volatility. In the second section, we investigate the predictive ability of average idiosyncratic volatility for excess market returns. In the third section, we examine the relation between idiosyncratic volatility and the cross-section of stock returns.

A. Time Trends

Our first set of empirical results examines the time trend in idiosyncratic volatility from 1926 to 1962. As discussed above, previous studies document a positive and robust trend for idiosyncratic volatility during 1962-1997. We test for a significant time trend in our holdout sample by fitting the following regression model:

$$VOL_t = \beta_0 + \beta_1 Trend_t + \beta_2 VOL_{t-1} + \beta_3 DepressionDummy_t + \beta_4 WWIIDummy_t + \varepsilon_t \quad (2)$$

where VOL_t represents $IVOL^{EW}$, $IVOL^{VW}$, $TOTVOL^{EW}$, or $TOTVOL^{VW}$, as described in Section III.B.2, VOL_{t-1} is the respective one-month lagged volatility value,[12] and $Trend_t$ is a time trend variable beginning with one (January, 1926) and ending with 438 (June, 1962). In some of our regressions, we also include two dummy variables corresponding to the Great Depression (1929-1933) and World War II (1939-1945) as a robustness check. We reported earlier (in Table 1) that our average idiosyncratic volatility measures are quite persistent. Hence, we use Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors.

We report our time trend findings (regression model (2)) in Table 2. The results in Panel A reveal a negative and significant time trend between 1926 and 1962 for all volatility measures. Whether we analyze equal-weighted or value-weighted, idiosyncratic or total volatility, there is a consistent downward trend in volatility during our sample period. These results are in sharp contrast to the upward trend in idiosyncratic volatility since 1962. To the best of our knowledge, this is the first empirical evidence of a significantly negative time trend over the 1926-1962 period based on daily returns data. The trend coefficients vary from -0.27×10^{-3}, for value-weighted idiosyncratic volatility with dummy variables included, to -1.22×10^{-3} for equal-weighted total volatility with dummy variables excluded. All trend coefficients become less negative, yet still significant, after we add the dummy variables, suggesting that our results are not driven by the Great Depression or World War II. The coefficients on the Depression dummy are positive and significant across all regressions, while the coefficients on WWII dummy are negative and mostly insignificant. The coefficients on lagged volatility are positive and significant, consistent with the evidence in Table 1 that our average idiosyncratic volatility measures are highly persistent.

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[12] We include lagged volatility to control for the persistence in volatility. Our trend results are stronger if we exclude lagged volatility from regression model (2).

Our Panel A findings suggest that the Great Depression caused a significant increase in both idiosyncratic and total volatility. To further ensure that our results are not driven by the Great Depression, we re-run our trend tests separately for the post-Depression period. The negative and significant trend coefficients in Panel B confirm that our previous negative trend results (Panel A) are not caused solely by the Depression. The trend coefficients vary between -0.43×10^{-3} for value-weighted idiosyncratic volatility and -2.29×10^{-3} for equal-weighted total volatility. The coefficients on lagged volatility continue to be positive and significant. We also note that, similar to the results in Panel A, the adjusted R^2 values are higher for the idiosyncratic volatility regressions compared to the total volatility regressions.

So far we have accounted for the persistence in idiosyncratic volatility by including lagged volatility in regression model (2) and by using Newey and West (1987) standard errors. However, Vogelsang (1998) argues that when regression errors are persistent, the Newey and West (1987) standard errors might still reject the null hypothesis of no trend too often. To address this problem, we report in Panel C the size-robust trend statistic (*t-PS*) developed by Vogelsang (1998).[13] Vogelsang shows that the *t-PS* test is valid in the presence of general forms of serial correlation in the errors of the trend function, with or without a unit root. Results in Panel C continue to show significant evidence of a downward trend in idiosyncratic volatility when we use the Vogelsang size robust trend statistic. This result is robust across measures of idiosyncratic volatility, and is stronger in the post-Depression period.

In summary, we document a negative and robust trend in idiosyncratic and total volatility between 1926 and 1962. This downward trend is in sharp contrast to the upward trend identified in the post-1962 period. Our findings can be useful in sorting out the various hypotheses attempting to explain the recent upward trend in idiosyncratic volatility. For example, if a

[13] We provide more details about this test statistic in the Appendix.

decline in firm age (Fink, Fink, Grullon, and Weston (2006)) or an increase in product market competition (Irvine and Pontiff (2005)) caused the post-1962 increase in idiosyncratic volatility, then one would expect to find opposite trends in the 1926-1962 period.

B. Predicting Market Returns

In this section, we examine the ability of average idiosyncratic and total volatility to forecast one-month-ahead excess returns on the market. As noted above, Goyal and Santa-Clara (2003) report evidence of forecasting ability while Bali, Cakici, Yan, and Zhang (BCYZ) (2005) claim that the relationship is unstable. We provide additional evidence on the average idiosyncratic volatility's forecasting ability by fitting the following regression to our 1926-1962 sample period:

$$\begin{aligned} MKTRF_{t+1} = \beta_0 + \beta_1 VOL_t + \beta_2 MKTRF_t + \beta_3 DP_t + \\ \beta_4 TERM_t + \beta_5 DEFAULT_t + \beta_6 RREL_t + \varepsilon_t \end{aligned} \tag{3}$$

where *MKTRF* is the return on the market minus the risk-free rate, *VOL* represents IVOL^{EW}, IVOL^{VW}, $\text{TOTVOL}^{\text{EW}}$, or $\text{TOTVOL}^{\text{VW}}$, as described in Section III.B.2, *DP* is the monthly dividend yield on the S&P 500 index, *TERM* is the difference between the 10-year Treasury bond yield and the 3-month Treasury bill rate, *DEFAULT* is the difference between Moody's Baa corporate bond yield and the10-year Treasury bond yield, and *RREL* is the current three-month T-bill rate minus its 12-month moving average.

In Panel A of Table 3, we report eight regression results based on four volatility measures, each with and without control variables. The first two columns show that neither equal-weighted nor value-weighted idiosyncratic volatility is able to forecast one-month-ahead market excess returns. None of the *t*-values associated with idiosyncratic volatility is greater than 0.56. Similarly, the next two columns (three and four) show that neither equal-weighted nor value-weighted total volatility is able to forecast one-month-ahead market excess returns. The adjusted R^2 values for these first four regressions never rise above 0.10%. We repeat this same process in columns five through eight after adding our five control variables. The lagged excess market return and dividend yield coefficients are positive and significant at conventional levels, but the coefficients on term spread, default spread, and relative short rates are insignificant. The main point, however, is that our volatility coefficients continue to be insignificant. Although the R^2 values improve to between 2.06% and 2.48% with the additional controls, none of the *t*-values associated with volatility is greater than 0.71.

In Panel B of Table 3, we show that our results are not driven by the Great Depression. We re-run all eight regressions using only the post-Depression period (1934-1962) and confirm that average idiosyncratic volatility, be it equal-weighted, value-weighted, idiosyncratic, or total, is unable to forecast one-month-ahead excess market returns. None of the *t*-values associated with our eight volatility coefficients is greater than 0.62 in absolute value, and none of the adjusted R^2 values is greater than 0.24%.

In summary, our finding that idiosyncratic volatility does not forecast excess market returns during 1926-1962 casts serious doubt on the stability of the relationship documented by Goyal and Santa-Clara (2003). While BCYZ (2005) and Wei and Zhang (2005) show that the idiosyncratic risk-return relation is not robust to the inclusion of more recent years, we find that the relation does not hold at all during an earlier 37-year period. While Goyal and Santa-Clara (2003) find a significant relationship between value-weighted excess returns and equal-weighted volatility for 1962-1999 and BCYZ (2005) show that such a relationship disappears for value-weighted idiosyncratic volatility, we find no significant relationship between market returns and average idiosyncratic volatility using either weighting scheme prior to 1962. Overall, our results contribute to the debate about the predictive ability of idiosyncratic volatility.

C. Cross-Sectional Stock Returns

In our third empirical section, we examine the relation between idiosyncratic volatility and cross-sectional stock returns. Although there is some controversy regarding previous findings related to idiosyncratic volatility and excess market returns, the Ang, Hodrick, Xing, and Zhang (AHXZ) (2006a) cross-sectional results constitute a veritable puzzle. Before searching for the underlying causes of the inverse relation between idiosyncratic volatility and cross-sectional returns, it would be useful to establish the robustness (or lack thereof) of this empirical result.

1. Characteristics of idiosyncratic and total volatility-sorted portfolios

We first examine the characteristics of portfolios sorted on volatility. We divide our sample stocks into quintiles based on the previous month's idiosyncratic volatility (*ivol*), defined as the standard deviation of the residuals in regression model (1), or total volatility (*totvol*), defined as the standard deviation of daily stock returns. For each volatility quintile portfolio, we report the mean value of the following firm characteristics: size rank gives the decile ranking of each stock based on its market capitalization; turnover is the monthly trading volume divided by total number of shares outstanding; percent of zero returns gives the percentage of daily returns that are zero for each firm during each month; Amihud's illiquidity rank gives the decile ranking based on Amihud's illiquidity measure;[14] and the past six-month return rank gives the decile ranking based on the past six-month stock returns.

Panel A of Table 4 contains the results for portfolios sorted by idiosyncratic volatility. The smallest quintile portfolio (Q1) has an average idiosyncratic volatility of 0.95%, and the largest quintile portfolio (Q5) has an average idiosyncratic volatility of 5.30%. There is a

[14] Amihud's (2002) price-impact illiquidity measure is calculated by dividing the absolute value of daily stock returns by daily dollar volume.

monotonically negative relation between the firm's size rank, as well as share price, and its idiosyncratic volatility. Our other firm characteristic variables, including turnover, percent of zero returns, Amihud's (2002) illiquidity rank, and the past six-month returns rank also exhibit strong cross-sectional patterns with respect to idiosyncratic volatility-sorted quintiles. Average monthly turnover increases from a low of 2.37% for the smallest quintile portfolio to 5.12% for the largest quintile portfolio. The percent of zero returns shows a general, albeit non-monotonic, increase from 20.87% to 27.10% from the smallest to the largest quintile portfolio. Amihud's (2002) illiquidity rank varies from a low of 3.21 for the smallest quintile to a high of 8.13 for the largest quintile. Our past six-month return ranks also exhibit a monotonic relation across idiosyncratic volatility quintiles. Past return ranks are highest in the smallest quintile at 5.73 and then steadily decline until reaching a low of 5.17 in the largest quintile.

Panel B reports the characteristics of firms sorted by total volatility (*totvol*). The results are very similar to those reported in Panel A. In summary, our Table 4 results reveal strong cross-sectional patterns across several firm characteristics. High idiosyncratic and total volatility firms tend to have low market capitalization, low stock price, high turnover, and high illiquidity (both in terms of zero percent returns and Amihud's (2002) illiquidity rank). They also tend to have lower past returns.

2. Performance of portfolios sorted on idiosyncratic volatility

We examine the performance of idiosyncratic volatility-sorted portfolios with respect to CAPM, Fama-French (1993, 1996), and Carhart (1997) models. Following AHXZ (2006a), in each month we divide all stocks into quintiles based on the previous month's idiosyncratic volatility (or total volatility). We then hold these portfolios for one month and calculate portfolio returns by using market-capitalization weights. For each quintile portfolio, we estimate the

CAPM alpha (α_{CAPM}), the Fama-French and Carhart alphas ($\alpha_{Fama\text{-}French}$ and $\alpha_{Carhart}$, respectively) using monthly portfolio returns from 1926 to 1962 as follows:

$$r_t = \alpha_{CAPM} + \beta\, MKTRF_t + \varepsilon_t \qquad (4)$$

$$r_t = \alpha_{Fama-French} + \beta_1 MKTRF_t + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_t \qquad (5)$$

$$r_t = \alpha_{Carhart} + \beta_1 MKTRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_t \qquad (6)$$

where r_t is monthly excess portfolio return, *MKTRF* is the excess market return, *SMB* and *HML* are returns on zero-investment factor-mimicking portfolios for size and book-to-market effects, and *UMD* is the return on the zero-investment factor-mimicking portfolio for one-year momentum in stock returns.

Panel A of Table 5 contains our empirical results for 1926-1962. Consistent with the anomalous findings reported in AHXZ (2006a), we confirm that firms with high idiosyncratic volatility are consistent underperformers, while firms with low idiosyncratic volatility consistently outperform risk adjusted returns. Between 1926 and 1962, low idiosyncratic volatility firms (Q1) achieved positive and significant alphas of 14, 15, and 14 basis points per month based on CAPM, Fama-French, and Carhart models, respectively. In contrast, high idiosyncratic volatility firms (Q5) obtained negative and significant alphas of -46, -53, and -70 basis points per month. The performance differentials between low and high idiosyncratic volatility portfolios (Q1-Q5) are positive and highly significant for each of our three models.

We report comparable total volatility results below the idiosyncratic volatility findings. Between 1926 and 1962, the low total volatility portfolio generated positive and significant alphas of 17, 18, and 15 basis points per month based on CAPM, Fama-French, and Carhart models, respectively. In contrast, high total volatility portfolios produced negative and significant alphas of -54, -60, and -79 basis points per month. The performance differentials between low and high total volatility portfolios are positive and highly significant.

In Panel B, we replicate all alpha estimates for the post-Depression period (i.e., 1934-1962) and find identical results; that is, all Q1 alphas are positive and significant, all Q5 alphas are negative and significant, and all Q1-Q5 differentials are positive and significant. Our Table 5 results reveal a stable, if puzzling, inverse relation between volatility and stock returns.

3. Portfolio performance sorted on idiosyncratic volatility and control variables

In this section, we investigate whether the inverse relation between idiosyncratic volatility and cross-sectional stock returns documented in Table 5 is driven by other firm characteristics. Specifically, we perform two-way sorts on idiosyncratic volatility and various firm characteristics including size, turnover, share price, percent of zero returns, Amihud's (2002) illiquidity measure, and past six-month returns. We report only the four-factor Carhart alphas due to space limitations, but CAPM and Fama-French alphas yield qualitatively similar results. The results in Panel A of Table 6 confirm the negative relation between stock performance and idiosyncratic volatility for four of five size-sorted portfolios. The only exception is the smallest size portfolio which exhibits declining performance as we move from Q1 to Q4 (as do all other size categories), but then the pattern reverses abruptly with a positive alpha of 52 basis points in Q5.

Three of five turnover-sorted portfolios (Panel B) and four of five share price-sorted portfolios (Panel C) confirm the same inverse relation between idiosyncratic volatility and stock performance. We find similar results for our liquidity measures in Panels D and E. Three of five zero return-sorted portfolios (Panel D) and four of five illiquidity-sorted portfolios (Panel E) exhibit the (now) expected inverse relation between idiosyncratic volatility and alpha. The lagged return results in Panel F show that the inverse volatility-alpha relationship is strongest for firms that performed well in the past six months (i.e., return quintiles 4 and 5). There is even some evidence of a positive volatility-alpha relationship for the poorest performing quintile.

Overall, the results in Table 6 show that idiosyncratic volatility-sorted portfolios capture much of the cross-sectional variation in stock performance. More importantly, our 1926-1962 sample confirms the same negative relation between idiosyncratic volatility and risk-adjusted returns documented in AHXZ's (2006a) 1963-2000 sample. Our Table 6 results also reveal a consistent pattern with respect to firm characteristics. The inverse relation between idiosyncratic volatility and excess returns is relatively strong across all portfolios except the smallest quintile portfolios with respect to firm size, turnover, share prices, and past returns, as well as the largest quintile portfolios based on percent of zero returns and illiquidity measures. This suggests that the inverse relation documented above is robust to all but the smallest, most illiquid, and poorest performing firms.

4. Cross-sectional regressions: stock returns on idiosyncratic volatility

In this subsection, we examine the relation between idiosyncratic volatility and stock returns using a cross-sectional regression approach. The advantage of this approach is that we are able to simultaneously control for firm characteristics that have been shown to impact the cross-section of stock returns. We fit regression model (7) to our data and report the results in Table 7.

$$\begin{aligned} r_t = \beta_0 + \beta_1 Vol_{t-1} + \beta_2 Beta_t + \beta_3 LogSize_{t-1} + \beta_4 PastReturn_{t-6} \\ + \beta_5 Turnover_{t-1} + \beta_6 Illiquidity_{t-1} + \beta_7 \%ZeroReturns_{t-1} + \varepsilon_t \end{aligned} \tag{7}$$

where r_t is monthly excess stock return. As before, we first estimate idiosyncratic volatility of each firm for each month as the standard deviation of market model regression residuals using daily returns. We calculate total volatility of each firm for each month as the standard deviation of daily stock returns. We also estimate *Beta* from a market model using daily stock returns.[15] *Vol* can refer to the firm's idiosyncratic volatility or its total volatility, depending on the specific regression. *Size* is the firm's market capitalization, *PastReturn* refers to the previous six-month return, and *Turnover* is the monthly trading volume divided by total number of shares outstanding. The *%ZeroReturns* variable measures the percentage of daily returns that are zero for each firm during each month, and *Illiquidity* is Amihud's (2002) illiquidity measure. We report the average coefficients of 432 monthly cross-sectional regressions. We report *t*-statistics based on Fama and MacBeth (1973) standard errors.

Our full sample (1926-1962) results in Panel A strongly confirm the negative cross-sectional relation between lagged idiosyncratic volatility and stock returns. Consistent with AHXZ (2006b), we find a negative and significant coefficient on both idiosyncratic volatility (columns one through four) and total volatility (columns five through eight). The negative relation increases in magnitude and significance as we add control variables from columns one to four. For the full model in column four, the lagged idiosyncratic volatility coefficient is -0.28, the related *t*-value is -5.73, and the average R^2 is 11.20%. We find the same pattern for total volatility as we add control variables in columns five through eight. Turning to the full model in column eight, we observe a lagged total volatility coefficient of -0.29, *t*-value of -5.73, and average R^2 of 11.32%. The coefficients on control variables are statistically significant and generally consistent with expectations. We find a positive relation between returns and beta, illiquidity, and zero returns; and a negative relation between returns and firm size, past returns and turnover. Our finding of a negative coefficient on past returns is inconsistent with the existence of return momentum, but is consistent with Jegadeesh and Titman's (1993) finding that profits to momentum strategies are substantially lower or even negative prior to 1965.

[15] We follow Ang, Hodrick, Xing, and Zhang (2006b) and use the contemporaneous beta in regression (7).

Our results in Panel B verify the same coefficient signs, orders of magnitude, and significance levels for the post-Depression period. Although there was a huge disruption in the real economy and financial markets during the Depression period, our volatility-return results are robust to these changes. The lagged idiosyncratic volatility coefficient is -0.29 for the full model in column four; its *t*-value is -5.34 and average R^2 is 11.24%. The lagged total volatility coefficient is -0.30 for the full model in column eight; its *t*-value is -5.07 and average R^2 is 11.39%. As in Panel A, the coefficients on control variables are consistent with expectations and generally statistically significant. There is a positive relation between returns and beta, illiquidity, and zero returns, and a negative relation between returns and firm size, past returns and turnover.

Overall, our cross-sectional results strongly confirm the inverse relation between idiosyncratic volatility and stock returns documented by AHXZ (2006a and 2006b) for the period from 1963 to 2000. The combination of their results based on a 38-year period with our results based on a 37-year period leaves little doubt of the robustness of this relationship. Increases in idiosyncratic volatility have led to lower stock returns over a 75-year period beginning in 1926 and spanning the Great Depression, several major wars, and various stock market disruptions. The "substantive puzzle" first reported in AHXZ (2006a) does not vanish with a longer series of observations. Future research is needed to explain the underlying cause(s) of these findings.

V. Summary and Conclusions

The primary objective of our study is to re-examine the most prominent (if controversial) findings related to idiosyncratic volatility using an extended sample of daily stock returns from

1926 to 1962. A review of the literature reveals three main findings related to recent work on idiosyncratic volatility. Each of these findings is based primarily on post-1962 data. First, the level of idiosyncratic volatility has increased steadily from 1962 to 1997 (CLMX (2001)). Second, idiosyncratic volatility has the ability to predict future market returns from 1962 to 1999 (Goyal and Santa-Clara (2003)), although this finding is refuted by BCYZ (2005). Third, there exists a negative and significant relation between idiosyncratic volatility and cross-sectional returns from 1963 to 2000 (AHXZ (2006a)). While it is beyond the scope of this paper to resolve each of these issues, we contribute new evidence to the debate by examining a 37-year holdout period.

Our analysis generates several new results. First, we document a negative and significant trend for both idiosyncratic and total volatility between 1926 and 1962. This downward trend contrasts sharply with the upward trend found in the post-1962 period. We further show that this negative trend is not an artifact of the Great Depression or World War II. Instead, there is a pervasive downward movement in our data over most of the 37-year period. Second, we find no evidence that idiosyncratic volatility can forecast excess market returns during 1926-1962. This finding casts additional doubt on the stability of the relationship documented by Goyal and Santa-Clara (2003). Third, and perhaps most surprising, our 1926-1962 results strongly confirm the inverse relation between idiosyncratic volatility and cross-sectional returns first documented in AHXZ (2006a).

Our results contribute to the literature in several ways. The downward trend in idiosyncratic volatility from 1926 to 1962 can provide a useful testing ground for competing hypotheses regarding the post-1962 upward trend. If declining firm age (Fink, Fink, Grullon, and Weston (2006)), poor profitability (Wei and Zhang (2006)), rising product market competition (Irvine and Pontiff (2005)), or capital market development (Brown and Kapadia (2006)) caused the post-1962 increase in idiosyncratic volatility, then one would expect to find rising firm age, improved profitability, declining competition, and a deteriorating capital market from 1926 to 1962. This contribution mirrors that of Brandt, Brav, and Graham (2005, p. 20) who argue that their result "raises considerably the bar for potential explanations: it is necessary to explain both the sudden increase in idiosyncratic volatility throughout the 1990s and also a more sudden drop in idiosyncratic volatility over the past few years."

A second contribution is that we add considerable weight to the debate over whether average idiosyncratic volatility forecasts excess market returns. Regardless of whether we use equal- or value-weighted measures, we do not find any evidence of forecasting ability during our 37-year sample. Our main contribution, however, is the verification of a negative risk premium for idiosyncratic volatility in the cross-section. This is indeed a puzzling result. The combination of our 37-year holdout sample with AHXZ's (2006a) original sample means that idiosyncratic risk has generated negative average returns during a 75-year period beginning in 1926. Clearly, future research is needed to identify the source(s) of this well-documented empirical result.

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Appendix: Vogelsang (1998) Size Robust Trend Statistic

In testing for a significant trend in time series data, the standard approach is to assume a trend model of the form

$$y_t = \beta_1 + \beta_2 t + u_t \tag{A.1}$$

The null hypothesis is that β_2 is equal to zero.

The *t-PS* statistic proposed by Vogelsang (1998) is a *t*-statistic based on the following partial sums regressions:

$$\begin{aligned} &z_t = \beta_1 t + \beta_2\left(\left(t + t^2\right)/2\right) + S_t \\ &where\ z_t = \sum_{j=1}^{t} y_j \ and\ S_t = \sum_{j=1}^{t} u_j \end{aligned} \tag{A.2}$$

Let t_z denote the standard least squares *t*-statistics for testing whether β_2 is equal to zero in regression A.2. Let RSS_y denote the least squares sum of squared residuals from A.1, and RSS_J denote the sum of squared residuals from the following regression:

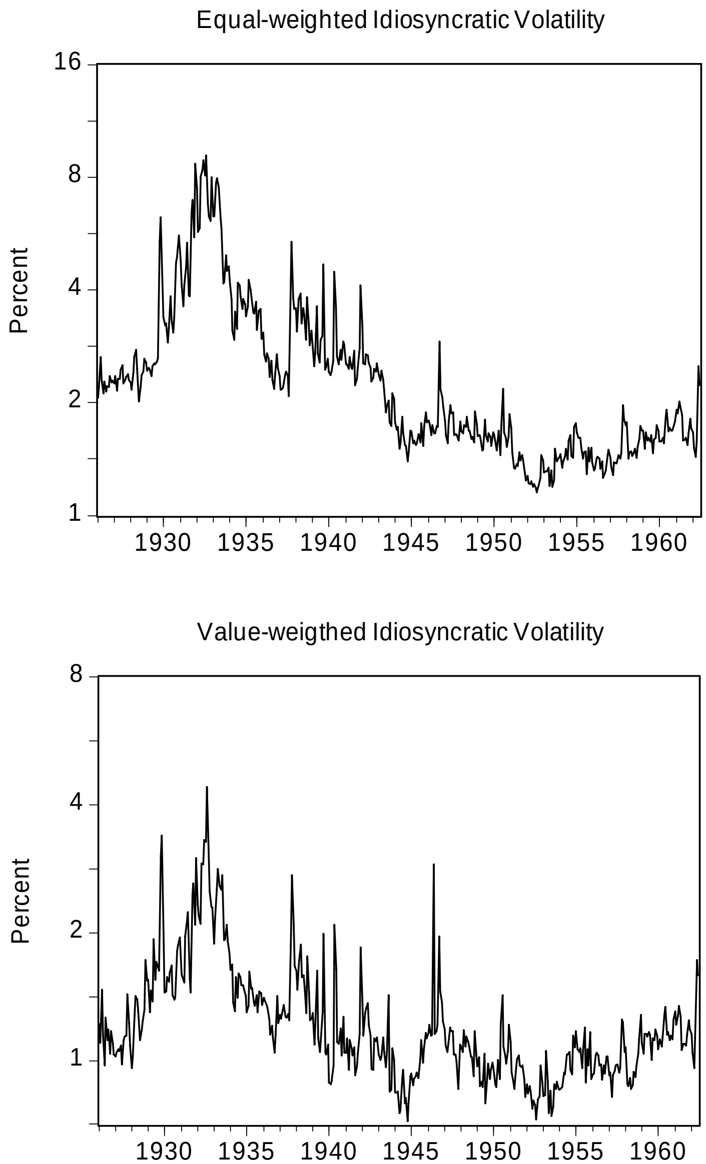
$$y_t = \beta_1 + \beta_2 t + \sum_{i=2}^{9} \beta_{i+1} t^i + u_t \tag{A.3}$$

Define $J_T = (RSS_y - RSS_J)/RSS_J$. Then the *t-PS* statistic is given by:

$$t - PS = T^{-1/2} t_z \exp\left(-bJ_T\right) \tag{A.4}$$

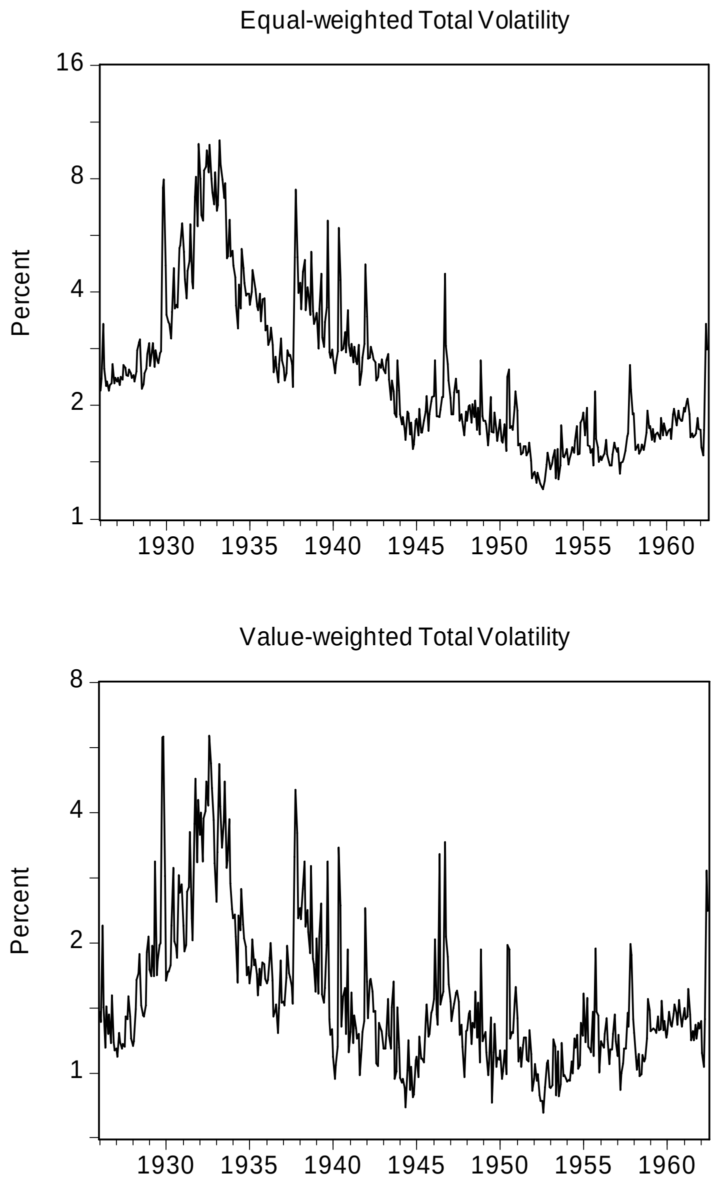
where T is the number of observations and b is a constant tabulated by Vogelsang associated with corresponding significance levels.

Figure 1
Average Idiosyncratic Volatility: 1926 - 1962



The sample period is 1926:01-1962:06. We obtain daily stock returns from the CRSP database. We estimate idiosyncratic volatility of each firm for each month as the standard deviation of market model regression residuals using daily returns. We calculate total volatility of each firm for each month as the standard deviation of daily stock returns. The top panel shows the equal-weighted average of idiosyncratic volatility across all firms. The bottom panel shows the market capitalization-weighted average of idiosyncratic volatility across all firms.

Figure 2
Average Total Volatility: 1926 - 1962



The sample period is 1926:01-1962:06. We obtain daily stock returns from the CRSP database. We estimate idiosyncratic volatility of each firm for each month as the standard deviation of market model regression residuals using daily returns. We calculate total volatility of each firm for each month as the standard deviation of daily stock returns. The top panel shows the equal-weighted average of total volatility across all firms. The bottom panel shows the market capitalization-weighted average of total volatility across all firms. All variables are expressed in percent.

Table 1
Descriptive Statistics for Average Idiosyncratic Volatility and Macroeconomic Variables

Our sample period is 1926:01-1962:06. We obtain daily stock returns, share prices, number of shares outstanding, and trading volume from the CRSP database. We obtain three-month Treasury bill rates, 10-year Treasury bond yields, and Moody's Baa corporate bond yields from the Federal Reserve Bank of St. Louis's website. We calculate term spread (TERM) as the difference between the 10-year Treasury bond yield and the 3-month Treasury bill rate. We calculate default spread (DEFAULT) as the difference between Moody's Baa corporate bond yield and the10-year Treasury bond yield. Relative short rate (RREL) is defined as the current three-month T-bill rate minus its 12-month moving average. We obtain monthly dividend yields (DP) for the S&P 500 index from Amit Goyal's website. We obtain monthly Fama and French (1993, 1996) factors as well as the momentum factor from Kenneth French's website. MKTRF is the market excess return. We estimate idiosyncratic volatility of each firm for each month as the standard deviation of market model regression residuals using daily returns. We calculate total volatility of each firm for each month as the standard deviation of daily stock returns. $IVOL^{EW}$ is the equal-weighted average of idiosyncratic volatility across all firms. $IVOL^{VW}$ is the market capitalization-weighted average of idiosyncratic volatility across all firms. $TOTVOL^{EW}$ is the equal-weighted average of total volatility across all firms. $TOTVOL^{VW}$ is the market capitalization-weighted average of total volatility across all firms. AR_1 is the first-order auto-correlation coefficient. All variables are expressed in percent.

Panel A: Univariate Summary Statistics (%)

	Mean	Median	Stdev	Max	Min	AR_1
$IVOL^{EW}$	2.48	1.95	1.44	9.15	1.15	0.94
$IVOL^{VW}$	1.27	1.13	0.48	4.39	0.72	0.84
$TOTVOL^{EW}$	2.76	2.21	1.66	10.12	1.20	0.90
$TOTVOL^{VW}$	1.64	1.34	0.86	6.00	0.81	0.80
MKTRF	0.82	1.34	6.48	38.18	-29.03	0.14
DP	5.12	4.87	1.65	15.36	2.80	0.95
TERM	1.52	1.69	0.95	3.24	-1.36	0.98
DEFAULT	1.88	1.35	1.23	7.59	0.52	0.98
RREL	-0.00	0.00	0.52	1.34	-1.83	0.91

Panel B: Correlations Among Volatility Measures

	$IVOL^{EW}$	$IVOL^{VW}$	$TOTVOL^{EW}$	$TOTVOL^{VW}$
$IVOL^{EW}$	1.00			
$IVOL^{VW}$	0.91	1.00		
$TOTVOL^{EW}$	0.99	0.92	1.00	
$TOTVOL^{VW}$	0.88	0.96	0.93	1.00

Panel C: Correlations Between Volatility and Macroeconomic Variables

	MKTRF	DP	TERM	DEFAULT	RREL
$IVOL^{EW}$	-0.04	0.49	0.42	0.93	-0.24
$IVOL^{VW}$	-0.05	0.34	0.28	0.78	-0.21
$TOTVOL^{EW}$	-0.09	0.47	0.42	0.90	-0.22
$TOTVOL^{VW}$	-0.16	0.35	0.29	0.75	-0.19

Table 2
Is There a Time Trend in Idiosyncratic Volatility?

Our sample period is 1926:01-1962:06. We obtain daily stock returns, share prices, number of shares outstanding, and trading volume from the CRSP database. We estimate idiosyncratic volatility of each firm for each month as the standard deviation of market model regression residuals using daily returns. We calculate total volatility of each firm for each month as the standard deviation of daily stock returns. $IVOL^{EW}$ is the equal-weighted average of idiosyncratic volatility across all firms. $IVOL^{VW}$ is the market capitalization-weighted average of idiosyncratic volatility across all firms. $TOTVOL^{EW}$ is the equal-weighted average of total volatility across all firms. $TOTVOL^{VW}$ is the market capitalization-weighted average of total volatility across all firms. Depression dummy is an indicator variable for the Great Depression which is equal to 1 for all months during 1929-1933. WWII dummy is an indicator variable for the World War II which is equal to 1 for all months during 1939-1945. In Panels A and B, numbers in parentheses are the *t*-statistics based on Newey and West (1987) standard errors. In Panel C, we provide *t-PS* using Vogelsang (1998) robust trend test. Coefficients on time trend that are statistically significant at 5 percent level are in bold. All volatility variables are expressed in percent.

Panel A: 1926 – 1962

	Independent Variables					
Dependent Variable	Intercept	Trend ($\times 10^{-3}$)	Lagged Volatility	Depression Dummy	WWII Dummy	Adjusted R^2
$IVOL^{EW}$	0.42	**-0.73**	0.90			0.88
	(3.78)	(-3.35)	(30.22)			
$IVOL^{EW}$	0.50	**-0.63**	0.83	0.43	-0.01	0.88
	(4.07)	(-3.16)	(21.71)	(2.72)	(-0.01)	
$IVOL^{VW}$	0.36	**-0.39**	0.79			0.70
	(3.85)	(-3.29)	(13.03)			
$IVOL^{VW}$	0.47	**-0.27**	0.65	0.29	-0.05	0.73
	(4.74)	(-2.74)	(9.26)	(3.81)	(-1.97)	
$TOTVOL^{EW}$	0.70	**-1.22**	0.84			0.82
	(4.12)	(-3.51)	(22.01)			
$TOTVOL^{EW}$	0.79	**-1.01**	0.76	0.65	-0.01	0.82
	(4.60)	(-3.36)	(16.75)	(2.93)	(-0.08)	
$TOTVOL^{VW}$	0.59	**-0.78**	0.75			0.65
	(4.89)	(-3.45)	(14.17)			
$TOTVOL^{VW}$	0.69	**-0.49**	0.61	0.56	-0.08	0.68
	(6.35)	(-2.74)	(10.69)	(3.75)	(-2.11)	

Panel B: 1934 – 1962

	Independent Variable			
Dependent Variable	Intercept	Trend ($\times 10^{-3}$)	Lagged Volatility	Adjusted R^2
$IVOL^{EW}$	0.81	**-1.26**	0.77	0.82
	(3.99)	(-3.26)	(15.32)	
$IVOL^{VW}$	0.57	**-0.43**	0.59	0.45
	(3.84)	(-2.57)	(5.85)	
$TOTVOL^{EW}$	1.40	**-2.29**	0.65	0.72
	(4.98)	(-4.03)	(11.21)	
$TOTVOL^{VW}$	0.81	**-0.83**	0.58	0.45
	(5.55)	(-3.43)	(7.86)	

Panel C: Vogelsang (1998) Robust Trend Test

	$VOL_t = \alpha + \beta \times Trend + e_t$			
Dependent Variable	α	β ($\times 10^{-5}$)	*t-PS*	Adjusted R^2
1926-1962				
$IVOL^{EW}$	3.98	-6.84	-1.66	0.36
$IVOL^{VW}$	1.66	**-1.83**	-2.03	0.23
$TOTVOL^{EW}$	4.44	**-7.68**	-1.80	0.35
$TOTVOL^{VW}$	2.32	**-3.09**	-2.04	0.21
1934-1962				
$IVOL^{EW}$	3.06	**-5.87**	-2.25	0.56
$IVOL^{VW}$	1.32	**-1.12**	-2.12	0.16
$TOTVOL^{EW}$	3.47	**-6.96**	-3.00	0.51
$TOTVOL^{VW}$	1.78	**-2.12**	-2.33	0.18

Table 3
Forecasting One-Month-Ahead Market Excess Returns Using Average Idiosyncratic Volatility

Our sample period is 1926:01-1962:06. We obtain stock returns, share prices, number of shares outstanding, and trading volume from the CRSP database. We obtain three-month Treasury bill rates, 10-year Treasury bond yields, and Moody's Baa corporate bond yields from the Federal Reserve Bank of St. Louis's website. We calculate term spread (TERM) as the difference between the 10-year Treasury bond yield and the 3-month Treasury bill rate. We calculate default spread (DEFAULT) as the difference between Moody's Baa corporate bond yield and the10-year Treasury bond yield. Relative short rate (RREL) is defined as the current three-month T-bill rate minus its 12-month moving average. We obtain monthly dividend yields (DP) for the S&P 500 index from Amit Goyal's website. We obtain monthly Fama and French (1993, 1996) factors as well as the momentum factor from Kenneth French's website. MKTRF is the market excess return. We estimate idiosyncratic volatility of each firm for each month as the standard deviation of market model regression residuals using daily returns. We calculate total volatility of each firm for each month as the standard deviation of daily stock returns. $IVOL^{EW}$ is the equal-weighted average of idiosyncratic volatility across all firms. $IVOL^{VW}$ is the market capitalization-weighted average of idiosyncratic volatility across all firms. $TOTVOL^{EW}$ is the equal-weighted average of total volatility across all firms. $TOTVOL^{VW}$ is the market capitalization-weighted average of total volatility across all firms. The dependent variable is the one-month-ahead market excess return. All variables are expressed in percent. Numbers in parentheses are *t*-statistics based on Newey and West (1987) standard errors.

Panel A: 1926-1962

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.18	0.30	0.20	0.59	-2.06	-2.11	-2.12	-2.03
	(0.18)	(0.21)	(0.21)	(0.54)	(-1.20)	(-1.09)	(-1.21)	(-1.07)
$IVOL^{EW}$	0.26				0.61			
	(0.56)				(0.61)			
$IVOL^{VW}$		0.41				0.32		
		(0.32)				(0.25)		
$TOTVOL^{EW}$			0.22				0.62	
			(0.54)				(0.71)	
$TOTVOL^{VW}$				0.14				0.22
				(0.18)				(0.24)
MKTRF					0.16	0.16	0.17	0.17
					(1.75)	(1.73)	(1.84)	(1.71)
DP					0.51	0.53	0.53	0.53
					(1.75)	(1.88)	(1.83)	(1.89)
TERM					-0.01	0.02	-0.04	0.02
					(-0.02)	(0.06)	(-0.11)	(0.05)
DEFAULT					-0.74	-0.19	-0.82	-0.21
					(-0.62)	(-0.28)	(-0.76)	(-0.34)
RREL					0.28	0.26	0.25	0.25
					(0.27)	(0.26)	(0.25)	(0.26)
Adj. R-squared	0.10%	-0.14%	0.10%	-0.20%	2.28%	2.06%	2.48%	2.07%

Panel B: 1934-1962

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.51	1.26	0.66	1.18	-1.17	-0.41	-0.86	-0.41
	(0.63)	(0.83)	(0.86)	(1.08)	(-0.75)	(-0.18)	(-0.61)	(-0.24)
$IVOL^{EW}$	0.21				0.71			
	(0.49)				(0.62)			
$IVOL^{VW}$		-0.28				-0.43		
		(-0.19)				(-0.25)		
$TOTVOL^{EW}$			0.12				0.13	
			(0.34)				(0.17)	
$TOTVOL^{VW}$				-0.17				-0.40
				(-0.20)				(-0.37)
MKTRF					-0.02	-0.02	-0.02	-0.03
					(-0.18)	(-0.29)	(-0.19)	(-0.37)
DP					0.32	0.31	0.32	0.31
					(1.42)	(1.32)	(1.43)	(1.36)
TERM					0.26	0.47	0.40	0.48
					(0.49)	(0.93)	(0.75)	(0.93)
DEFAULT					-0.86	-0.27	-0.45	-0.22
					(-0.84)	(-0.45)	(-0.51)	(-0.35)
RREL					-1.01	-0.80	-0.87	-0.78
					(-1.87)	(-1.67)	(-1.69)	(-1.64)
Adj. R-squared	-0.17%	-0.27%	-0.23%	-0.26%	0.24%	0.07%	0.05%	0.13%

Table 4
Firm Characteristics of Portfolios Sorted By Idiosyncratic Volatility

Our sample period is 1926:01-1962:06. We obtain stock returns, share prices, number of shares outstanding, and trading volume from the CRSP database. We estimate idiosyncratic volatility of each firm for each month as the standard deviation of market model regression residuals using daily returns. We calculate total volatility of each firm for each month as the standard deviation of daily stock returns. Size rank gives the decile ranking based on market capitalization. Turnover is the monthly trading volume divided by total number of shares outstanding. Percent of zero returns gives the percentage of daily returns that are zero for each firm during each month. Amihud's illiquidity rank gives the decile ranking based on Amihud's illiquidity measure. Past six-month return rank gives the decile ranking based on past six-month stock returns. Each month, we divide all stocks into quintiles based on past month idiosyncratic or total volatility. We report the time-series average of the cross-sectional average for each idiosyncratic or total volatility portfolio.

Panel A: Idiosyncratic Volatility

	Idiosyncratic Volatility Quintiles				
	Q1-low	Q2	Q3	Q4	Q5-high
Idiosyncratic Volatility (%)	0.95	1.46	1.97	2.71	5.30
Size Rank	7.78	6.64	5.64	4.51	2.92
Share Price ($)	56.35	39.66	31.64	24.28	15.36
Turnover (%)	2.37	3.81	4.25	4.62	5.12
Percent of Zero Returns	20.87	18.91	19.60	21.47	27.10
Amihud's Illiquidity Rank	3.21	4.34	5.35	6.47	8.13
Past six-month Return Rank	5.73	5.65	5.55	5.41	5.17
Average Number of Stocks	169	169	169	169	169

Panel B: Total Volatility

	Total Volatility Quintiles				
	Q1-low	Q2	Q3	Q4	Q5-high
Total Volatility (%)	1.12	1.74	2.29	3.04	5.55
Size Rank	7.39	6.55	5.76	4.72	3.08
Share Price ($)	54.72	39.85	32.24	24.82	15.70
Turnover (%)	1.66	3.24	4.46	5.21	5.60
Percent of Zero Returns	22.95	19.36	19.06	20.49	26.11
Amihud's Illiquidity Rank	3.71	4.54	5.22	6.15	7.89
Past six-month Return Rank	5.67	5.60	5.53	5.44	5.25
Average Number of Stocks	169	169	169	169	169

Table 5
Alphas of Portfolios Sorted by Idiosyncratic Volatility

Our sample period is 1926:01-1962:06. We obtain stock returns, share prices, number of shares outstanding, and trading volume from the CRSP database. We estimate idiosyncratic volatility of each firm for each month as the standard deviation of market model regression residuals using daily returns. We calculate total volatility of each firm for each month as the standard deviation of daily stock returns. We obtain monthly Fama and French (1993, 1996) factors as well as the momentum factor from Kenneth French's website. Each month, we divide all stocks into quintiles based on past month idiosyncratic volatility or total volatility. We then hold these portfolios for one month and calculate portfolio returns by using market-capitalization weight. For each portfolio, we estimate three alpha measures. CAPM alpha is based on the CAPM model. Fama-French alpha is based on the Fama and French (1993, 1996) three-factor model. Carhart alpha is based on the Carhart (1997) four-factor model. All alphas are expressed in percent. Numbers in parentheses are *t*-statistics.

Panel A: 1926-1962

	Idiosyncratic Volatility Quintiles					
	Q1-low	Q2	Q3	Q4	Q5-high	Q1-Q5
CAPM alpha	0.14	-0.08	-0.12	-0.22	-0.46	**0.60**
	(3.93)	(-1.23)	(-1.22)	(-1.44)	(-1.85)	(2.24)
Fama-French alpha	0.15	-0.09	-0.15	-0.27	-0.53	**0.68**
	(5.11)	(-1.49)	(-1.98)	(-2.67)	(-2.67)	(3.31)
Carhart alpha	0.14	-0.04	-0.03	-0.21	-0.70	**0.84**
	(4.67)	(-0.69)	(-0.40)	(-2.01)	(-3.49)	(4.04)

	Total Volatility Quintiles					
	Q1-low	Q2	Q3	Q4	Q5-high	Q1-Q5
CAPM alpha	0.17	0.14	-0.13	-0.30	-0.54	**0.71**
	(3.28)	(2.33)	(-1.31)	(-1.85)	(-2.22)	(2.70)
Fama-French alpha	0.18	0.14	-0.16	-0.34	-0.60	**0.79**
	(3.76)	(2.34)	(-1.83)	(-2.85)	(-3.08)	(3.79)
Carhart alpha	0.15	0.19	-0.06	-0.30	-0.79	**0.94**
	(3.06)	(3.22)	(-0.75)	(-2.42)	(-4.00)	(4.47)

Panel B: 1934-1962

	Idiosyncratic Volatility Quintiles					
	Q1-low	Q2	Q3	Q4	Q5-high	Q1-Q5
CAPM alpha	0.13	-0.08	-0.12	-0.24	-0.48	**0.61**
	(3.99)	(-1.60)	(-1.47)	(-1.77)	(-2.24)	(2.60)
Fama-French alpha	0.14	-0.09	-0.14	-0.27	-0.53	**0.67**
	(5.02)	(-1.83)	(-1.99)	(-2.95)	(-3.73)	(3.31)
Carhart alpha	0.14	-0.04	-0.03	-0.21	-0.70	**0.84**
	(4.67)	(-0.69)	(-0.40)	(-2.01)	(-3.49)	(4.38)

	Total Volatility Quintiles					
	Q1-low	Q2	Q3	Q4	Q5-high	Q1-Q5
CAPM alpha	0.19	0.09	-0.15	-0.39	-0.53	**0.72**
	(3.56)	(1.45)	(-1.70)	(-2.57)	(-2.53)	(3.00)
Fama-French alpha	0.20	0.08	-0.17	-0.43	-0.59	**0.78**
	(4.20)	(1.40)	(-2.42)	(-4.01)	(-4.05)	(4.83)
Carhart alpha	0.17	0.13	-0.13	-0.40	-0.54	**0.71**
	(3.53)	(2.26)	(-1.76)	(-3.60)	(-3.65)	(4.28)

Table 6
Alphas of Portfolios Sorted by Idiosyncratic Volatility and Controlling Variables

Our sample period is 1926:01-1962:06. We obtain stock returns, share prices, number of shares outstanding, and trading volume from the CRSP database. We estimate idiosyncratic volatility of each firm for each month as the standard deviation of market model regression residuals using daily returns. We calculate total volatility of each firm for each month as the standard deviation of daily stock returns. We obtain monthly Fama and French (1993, 1996) factors as well as the momentum factor from Kenneth French's website. Size is the firm's market capitalization. Turnover is the monthly trading volume divided by total number of shares outstanding. Percent of zero returns gives the percentage of daily returns that are zero for each firm during each month. Illiquidity gives the Amihud's illiquidity measure. Each month, we first divide all stocks into quintiles based on the control variable and then into five equal-size portfolios based on past month idiosyncratic volatility. We hold these portfolios for one month and calculate portfolio returns by using market-capitalization weight. For each portfolio, we estimate and report the Carhart alpha which is based on the Carhart (1997) four-factor model. All alphas are expressed in percent. Numbers in parentheses are *t*-statistics.

Panel A: Size

	Idiosyncratic Volatility Quintiles					
Size Quintiles	Q1-low	Q2	Q3	Q4	Q5-high	Q1-Q5
1 (small)	0.68	0.61	0.48	0.07	0.52	0.16 (0.35)
2	0.44	0.47	0.24	-0.09	-0.79	**1.23** (5.11)
3	0.36	0.31	0.07	-0.22	-0.56	**0.91** (4.15)
4	0.25	0.11	0.04	-0.04	-0.28	**0.53** (3.03)
5 (large)	0.14	0.15	-0.07	-0.13	-0.45	**0.60** (4.11)

Panel B: Turnover

	Idiosyncratic Volatility Quintiles					
Turnover Quintiles	Q1-low	Q2	Q3	Q4	Q5-high	Q1-Q5
1 (low)	0.11	0.35	0.17	0.01	0.19	-0.08 (-0.19)
2	0.26	-0.04	-0.14	-0.20	-0.32	0.58 (1.59)
3	0.31	0.01	0.04	-0.02	-0.87	**1.18** (3.52)
4	0.28	-0.04	-0.18	-0.34	-1.04	**1.33** (4.15)
5 (high)	0.01	-0.22	-0.25	-0.42	-0.97	**0.97** (3.10)

Panel C: Share Price

	Idiosyncratic Volatility Quintiles					
Share Price Quintiles	Q1-low	Q2	Q3	Q4	Q5-high	Q1-Q5
1 (low)	0.51	0.50	0.03	-0.38	-0.01	0.52 (1.12)
2	0.11	-0.07	-0.05	-0.24	-0.84	**0.95** (3.45)
3	0.19	-0.01	-0.08	-0.15	-0.36	**0.55** (2.29)
4	0.17	-0.06	-0.09	-0.08	-0.41	**0.57** (2.99)
5 (high)	0.15	0.14	-0.07	-0.04	-0.52	**0.67** (3.56)

Panel D: Percent of Zero Returns						
	Idiosyncratic Volatility Quintiles					
Percent of Zero Return Quintiles	Q1-low	Q2	Q3	Q4	Q5-high	Q1-Q5
1 (low)	0.15	-0.10	-0.24	-0.42	-0.70	**0.85** (3.55)
2	0.05	0.09	0.04	-0.49	-0.72	**0.77** (3.00)
3	0.03	0.01	-0.25	0.01	-0.70	**0.73** (2.39)
4	0.24	0.18	0.10	-0.30	-0.35	0.59 (1.68)
5 (high)	0.27	0.30	0.24	0.42	0.21	0.06 (0.10)

Panel E: Illiquidity						
	Idiosyncratic Volatility Quintiles					
Illiquidity Quintiles	Q1-low	Q2	Q3	Q4	Q5-high	Q1-Q5
1 (liquid)	0.17	0.17	-0.12	-0.24	-0.42	**0.58** (3.46)
2	0.21	0.13	0.07	-0.13	-0.47	**0.68** (3.44)
3	0.14	0.31	-0.11	-0.11	-0.42	**0.56** (2.74)
4	0.35	0.35	0.09	-0.33	-0.79	**1.14** (3.98)
5 (illiquid)	0.47	0.56	-0.06	0.71	-0.15	0.63 (1.23)

Panel F: Past Six-month Return						
	Idiosyncratic Volatility Quintiles					
Past Six-month Return Quintiles	Q1-low	Q2	Q3	Q4	Q5-high	Q1-Q5
1 (losers)	-0.13	-0.07	-0.18	-0.05	0.94	**-1.07** (-2.20)
2	0.02	-0.07	-0.37	-0.01	0.01	0.05 (0.02)
3	-0.08	-0.00	-0.10	-0.09	-0.41	0.33 (1.17)
4	0.32	0.07	-0.15	-0.05	-0.44	**0.75** (2.53)
5 (winners)	0.30	-0.02	-0.09	-0.46	-1.37	**1.61** (4.52)

Table 7
Cross-Sectional Regressions of Stock Returns on Idiosyncratic Volatility

Our sample period is 1926:07-1962:06. We obtain daily stock returns, share prices, number of shares outstanding, and trading volume from the CRSP database. We estimate idiosyncratic volatility of each firm for each month as the standard deviation of market model regression residuals using daily returns. We calculate total volatility of each firm for each month as the standard deviation of daily stock returns. We obtain monthly Fama and French (1993, 1996) factors as well as the momentum factor from Kenneth French's website. Beta is estimated from a market model using daily stock returns. Turnover is the monthly trading volume divided by total number of shares outstanding. Percent of zero returns gives the percentage of daily returns that are zero for each firm during each month. Illiquidity gives the Amihud's illiquidity measure. Each month, we first divide all stocks into quintiles based on the control variable and then into five equal-size portfolios based on past month idiosyncratic volatility. We hold these portfolios for one month and calculate portfolio returns by using market-capitalization weight. For each portfolio, we estimate and report the Carhart alpha which is based on the Carhart (1997) four-factor model. We report the average coefficients of 444 monthly cross-sectional regressions. All regressors except Beta are lagged one month. Beta is contemporaneous with the dependent variable. Numbers in parentheses are *t*-statistics based on Fama and MacBeth (1973) standard errors.

Panel A: 1926-1962

	Dependent Variable: Monthly Stock Excess Return (%)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.49	3.50	3.04	2.93	0.52	3.56	3.10	2.98
	(1.71)	(4.32)	(4.20)	(4.01)	(1.84)	(4.47)	(4.35)	(4.17)
Idiosyncratic Volatility	-0.08	**-0.20**	**-0.18**	**-0.28**				
	(-1.28)	(-3.84)	(-3.46)	(-5.73)				
Total Volatility					-0.09	**-0.22**	**-0.20**	**-0.29**
					(-1.53)	(-4.04)	(-3.73)	(-5.83)
Beta	0.69	0.70	0.68	0.77	0.73	0.75	0.72	0.81
	(5.50)	(5.61)	(5.88)	(6.82)	(5.96)	(6.05)	(6.28)	(7.25)
Log Market Cap		-0.29	-0.25	-0.25		-0.29	-0.26	-0.24
		(-4.58)	(-4.56)	(-4.65)		(-4.61)	(-4.59)	(-4.66)
Past Six-month Return			-0.01	-0.01			-0.01	-0.01
			(-3.34)	(-2.47)			(-3.37)	(-2.54)
Turnover				-0.04				-0.03
				(-3.50)				(-3.16)
Illiquidity				0.80				0.79
				(2.45)				(2.39)
% of Zero Returns				1.07				0.97
				(3.00)				(2.69)
Average R-Squared	6.52%	7.84%	9.27%	11.20%	6.59%	7.96%	9.37%	11.32%

Panel B: 1934-1962

	Dependent Variable: Monthly Stock Excess Return (%)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.73	3.18	2.97	2.93	0.75	3.26	3.05	2.99
	(3.32)	(5.06)	(5.27)	(5.34)	(3.44)	(5.33)	(5.55)	(5.62)
Idiosyncratic Volatility	-0.10	**-0.24**	**-0.21**	**-0.29**				
	(-1.45)	(-3.75)	(-3.33)	(-5.34)				
Total Volatility					-0.12	**-0.25**	**-0.23**	**-0.30**
					(-1.66)	(-3.94)	(-3.56)	(-5.07)
Beta	0.58	0.60	0.59	0.66	0.62	0.65	0.63	0.69
	(4.92)	(5.12)	(5.46)	(6.22)	(5.42)	(5.59)	(5.87)	(6.63)
Log Market Cap		-0.22	-0.20	-0.21		-0.25	-0.21	-0.21
		(-4.68)	(-4.81)	(-5.25)		(-3.94)	(-4.95)	(-5.36)
Past Six-month Return			-0.01	-0.01			-0.01	-0.01
			(-1.98)	(-1.28)			(-2.00)	(-1.35)
Turnover				-0.04				-0.04
				(-3.10)				(-2.78)
Illiquidity				0.82				0.80
				(2.00)				(1.95)
% of Zero Returns				1.07				1.00
				(3.18)				(2.87)
Average R-Squared	6.72%	8.05%	9.39%	11.24%	6.82%	8.20%	9.50%	11.39%