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Idiosyncratic Risk Matters!

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ABSTRACT

This paper takes a new look at the predictability of stock market returns with risk measures. We find a significant positive relation between average stock variance (largely idiosyncratic) and the return on the market. In contrast, the variance of the market has no forecasting power for the market return. These relations persist after we control for macroeconomic variables known to forecast the stock market. The evidence is consistent with models of time-varying risk premia based on background risk and investor heterogeneity. Alternatively, our findings can be justified by the option value of equity in the capital structure of the firms.

MOST ASSET PRICING MODELS, starting with Merton's (1973) ICAPM, suggest a positive relation between risk and return for the aggregate stock market. There is a long empirical literature that has tried to establish the existence of such a tradeoff between risk and return for stock market indices.[1] Unfortunately, the results have been inconclusive. Often the relation between risk and return has been found insignificant, and sometimes even negative.

The innovation in this paper is to look at average stock risk in addition to market risk. We measure average stock risk in each month similarly to Campbell et al. (2001; hereafter CLMX), as the cross-sectional average of the variances of all the stocks traded in that month. We then run predictive regressions of market returns on this variance measure as well as the variance of the market. Consistent with some previous studies, we find that market variance has no forecasting power for the market return. However, we do find a significant positive relation between average stock variance and the return on the market.

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[1] See, for example, Merton (1980), Pindyck (1984), Campbell (1987), French, Schwert, and Stambaugh (1987), Turner, Startz, and Nelson (1989), Baillie and DeGennaro (1990), Nelson (1991), Campbell and Hentschel (1992), Chan, Karolyi, and Stulz (1992), Glosten, Jagannathan, and Runkle (1993), Whitelaw (1994), and Scruggs (1998).

Since average stock risk is mostly driven by idiosyncratic risk, our results appear to be at odds with most models in financial economics that state that only systematic risk should affect returns. However, there are several asset pricing models in the literature that take idiosyncratic risk into account. Levy (1978), Merton (1987), and Malkiel and Xu (2001) build extensions of the CAPM where the investors, for some exogenous reason, hold undiversified portfolios.[2] The resulting pricing equation relates the returns of stocks to their beta with the market and their beta with respect to a market-wide measure of idiosyncratic risk. Mayers (1976) introduces a nontraded human capital factor in a CAPM setting and obtains a similar pricing relation. Barberis and Huang (2001) offer a different type of asset pricing model based on prospect theory, where investors are loss averse over the fluctuations of individual stocks that they own. They also obtain a relation between expected returns and idiosyncratic risk.

There has been a lively debate on the empirical evidence on the pricing of idiosyncratic risk in the cross section of stocks. In very early work, Douglas (1969) and Lintner (1965) find that the variance of the residuals from a market model is strongly significant in explaining the cross section of average stock returns, but Miller and Scholes (1972) and Fama and Macbeth (1973) point out some statistical pitfalls in the analysis. However, Lehmann (1990) reaffirms the results of Douglas after conducting a careful econometric analysis. Malkiel and Xu (1997, 2001) also present evidence of the importance of idiosyncratic risk in explaining the cross section of expected stock returns, even after controlling for size. In a different context, Bessembinder (1992) finds support for pricing of idiosyncratic risk in futures markets that is consistent with Hirshleifer's (1988) model of fixed costs of participation. Green and Rydqvist (1997) present an interesting study of the pricing of Swedish lottery bonds and find that these bonds command a premium for a risk that is idiosyncratic by construction.

Our paper is about the time-series relation between average stock risk and the stock market return. It is *not* about cross-sectional pricing of stocks, although the two aspects are, of course, related. There are several potential justifications for the dynamic relation that we document.

One possible explanation for our findings is that investors hold nontraded assets which add background risk to their traded portfolio decisions. When the risk of the nontraded assets increases, the investors are less willing to hold other

[2] There are rational and irrational justifications for limited diversification. Transaction costs and taxes restrict the portfolio holdings of investors. Employee compensation plans often give workers stock in their firms but restrict their capacity to sell their holdings, thereby leading to a concentrated exposure. Private information is another motive for holding large positions. Barber and Odean (2000) report that the mean household's portfolio contains only 4.3 stocks (worth 47,334 dollars), and the median household invests in 2.61 stocks (worth 16,210 dollars). Goetzmann and Kumar (2001) and Polkovnichenko (2001) provide additional evidence on the lack of diversification of the equity portfolios of individual investors. Benartzi (2001) and Benartzi and Thaler (2001) document that individuals hold a disproportionate amount of their pension plans in the stock of the company they work for. Huberman (2001) surveys evidence that investors are prone to investing in familiar stocks and ignore portfolio diversification.

traded risky assets.[3] The investors then require an increase in expected return to be persuaded to hold the market portfolio of traded stocks. As long as the riskiness of the nontraded assets is related to the total risk of individual stocks, we would obtain a trade-off between market return and average stock risk.

There are two prominent examples of nontraded assets that have been widely studied in the literature: (1) human capital, and (2) private businesses. For both of these nontraded assets, it seems reasonable that their riskiness should be related to the total riskiness of the average traded stock. To the extent that human capital is firm specific, its value should fluctuate with the value of the company that employs the worker. More obviously, private businesses are likely to be similar in risk to small traded firms. Human capital and private businesses constitute a large part of the portfolio of investors. Heaton and Lucas (1997, 2000) find that entrepreneurial income is a large source of undiversifiable risk that is closely correlated with common stock returns.[4] Storesletten, Telmer, and Yaron (2001) show that idiosyncratic risk in labor income helps explain equity returns. Vissing-Jørgensen and Moskowitz (2002) report that private equity capital was worth more than public equity in the United States until 1995 and is still of the same order of magnitude today. Further, they find that over 45 percent of the net worth of investors with private businesses consists of private equity. Of this, more than 70 percent is concentrated in a single firm, implying that they hold very undiversified portfolios. Finally, these investors are likely to have an impact in the market since they hold over 12 percent of the total public equity in the United States.

Our results are also consistent with the model of Constantinides and Duffie (1996). In their model, investors are subject to idiosyncratic income shocks, and equilibrium risk premia depend on the cross-sectional variance of consumption growth among investors. We show that our measure of average stock risk is intimately related to the cross-sectional dispersion of stock returns. If we assume that individual stocks proxy for the idiosyncratic income of investors, we can interpret average stock risk as a measure of the cross-sectional variance of income shocks among investors. As emphasized by Constantinides (2002), for models based on heterogeneity to explain the market risk premium, income shocks must be persistent and display countercyclical conditional variance. Interpreting individual stock returns as proxies for idiosyncratic income shocks satisfies both conditions. Individual stock prices are persistent (in fact, being asset prices, they are integrated) and we show in the paper that their average variance is countercyclical. Jacobs and Wang (2001) provide evidence that the variance of consumption growth across individuals is a priced factor in the cross section of stock returns. Sarkissian (2001) finds that cross-country dispersion matters for exchange rate premia.

[3] This would be true for most standard preferences, as long as the traded assets are not negatively correlated with the nontraded assets. The increase in background risk is isomorphic to an increase in risk aversion from the standpoint of the investor's stock portfolio allocation (see Gollier (2001)).

[4] Jagannathan and Wang (1996) emphasize the importance of labor income risk in their tests of the conditional CAPM. Heaton and Lucas (2000) extend their work by showing that both labor and proprietary income are important for asset pricing.

A different explanation for the impact of average stock volatility on stock returns follows from viewing equity and debt as contingent claims on the assets of the company. Following Black and Scholes (1973) and Merton (1974), we can think of the equity in a firm as a call option on the value of the firm's assets. Then, as the volatility of the assets increases, the value of the equity goes up at the expense of the debtholders. The relation between average stock variance and market return (which is an average of the returns to all individual stocks) follows from this idea since average stock variance mostly reflects the variance of the assets.[5] Using this idea, Campbell and Taksler (2002) find that the correlation between average stock variance and the spread of an index of A-rated bonds over Treasuries is 0.7 in a sample from 1965 to 1999. This positive correlation is consistent with a *negative* impact of average stock variance on corporate bond returns and a *positive* impact on equity returns. Under this explanation, an increase in idiosyncratic risk would not have an impact on the total value of the assets of firms, only on the split of that value between equity and debt.

Our analysis proceeds as follows. In Section I, we discuss the measures of market risk and average stock risk and present the main findings about the predictive ability of average stock risk for the stock market. To confirm the predictability results, we run a battery of robustness checks in Section II. We implement a bootstrap experiment to check the small sample properties of our regressions, extend the sample, and control for business cycle fluctuations. The appendix provides details on further robustness checks. To assess the economic significance of the predictability of stock returns, Section III constructs a trading strategy based on out-of-sample forecasts of the market using the risk measures. Section IV concludes.

I. Main Results

In this section, we introduce our risk measures and investigate their relation to the market return. We find that the variance of the market has no forecasting power for the market return. In contrast, we find a significant positive relation between average stock variance and the return on the market.

A. Risk Measures

Each month, we compute the monthly variance of a portfolio p using within-month daily return data as

$$V_{pt} = \sum_{d=1}^{D_t} r_{pd}^2 + 2\sum_{d=2}^{D_t} r_{pd} r_{pd-1}, \tag{1}$$

where D_t is the number of days in month t and r_{pd} is the portfolio's return on day d. The second term on the right-hand side adjusts for the autocorrelation in daily returns using the approach proposed by French et al. (1987). Similarly, we

[5] We caution the reader that our measure of average stock variance is an imperfect proxy for asset variance. Assuming that corporate debt is risk free, equity variance is equal to asset variance multiplied by the square of one plus the debt–equity ratio. The relation between asset variance and equity variance thus depends on the average debt–equity ratio.

compute the average stock variance as the arithmetic average of the monthly variance of each stock's returns

$$V_t = \frac{1}{N_t}\sum_{i=1}^{N_t}\left[\sum_{d=1}^{D_t} r_{id}^2 + s\sum_{d=2}^{D_t} r_{id}r_{id-1}\right], \tag{2}$$

where r_{id} is the return on stock i in day d and N_t is the number of stocks that exist in month t.[6] Note that this is not, strictly speaking, a variance measure since we do not demean returns before taking the expectation. However, for short holding periods, the impact of subtracting the means is minimal. Even for monthly excess returns, the expected squared return overstates the variance by less than one percent of its level.[7] The advantage of this approach, of course, is that it allows us to sidestep the issue of estimating the mean stock returns.

Our measure, V_t, approximates the variance of a stock by its squared return. This is a measure of total risk, including both systematic and idiosyncratic components. To better understand the risk measures, assume that the return of each stock i is driven by a common factor f and a firm-specific shock ε_i. To simplify the exposition, assume the factor loading for each stock is one, ignore the serial correlation adjustment in equation (2), and use the equal-weighted portfolio as a proxy for the market.[8] The daily returns are generated by

$$r_{id} = f_d + \varepsilon_{id}, \tag{3}$$

$$r_{ewd} = \frac{1}{N_t}\sum_{i=1}^{N_t} r_{id} = f_d + \frac{1}{N_t}\sum_{i=1}^{N_t}\varepsilon_{id}. \tag{4}$$

Assume further that the idiosyncratic shocks and the factor shocks are uncorrelated. This implies that

$$V_t = \sum_{i=1}^{D_t}\left[\frac{1}{N_t}\sum_{i=1}^{N_t} r_{id}^2\right] = \sum_{i=1}^{D_t}\left[f_d^2 + \frac{2}{N_t}f_d\sum_{i=1}^{N_t}\varepsilon_{id} + \frac{1}{N_t}\sum_{i=1}^{N_t}\varepsilon_{id}^2\right], \tag{5}$$

[6] Note that if the autocorrelation of returns is less than -0.5, then the second term dominates and makes the variance estimate negative. Although this is never the case with portfolio volatility, it sometimes occurs (on average for five percent of the cases) for individual stocks. For these stocks, we ignore the second term and, instead, calculate the stock variance as the sum of squared returns only. We have tried the alternative approach of using up to 10 lags to correct for higher-order serial dependence and found no impact in the average variance measure. Finally, stocks with less than five trading days in a month are excluded from computations for that month.

[7] The computation is based on a typical stock mean return of 1.08 percent and a standard deviation of 16.53 percent (Table I). The results of the regressions reported in the Subsection I.C also do not change if we use an alternative measure of average stock variance adjusted for the mean. Using daily data, French et al. (1987) and Schwert (1989) also find the squared mean term is irrelevant to calculate variances.

[8] This discussion is only for illustration purposes. The results can easily be generalized to include many factors and different factor loadings for different stocks. We use the equal-weighted portfolio to avoid having to deal with market capitalization weights in the measures of volatility.

$$V_{ewt} = \sum_{i=1}^{D_t} r_{ewd}^2 = \sum_{i=1}^{D_t} \left[f_d^2 + \frac{2}{N_t} f_d \sum_{i=1}^{N_t} \varepsilon_{id} + \left(\frac{1}{N_t} \sum_{i=1}^{N_t} \varepsilon_{id} \right)^2 \right]. \tag{6}$$

The first two terms of equation (6) are the same as those of equation (5). However, the contribution of the idiosyncratic component is divided further by the number of stocks in equation (6). For a large cross section, the last term is negligible in equation (6) but not in equation (5). Denoting the mean and variance of the factor by μ_f and σ_f^2, and assuming the idiosyncratic shocks are i.i.d. across stocks with variance σ_ε^2, we get:

$$E[V_t] = \sum_{i=1}^{D_t} \left[E[f_d^2] + \frac{1}{N_t} \sum_{i=1}^{N_t} E[\varepsilon_{id}^2] \right] = D_t[(\mu_f^2 + \sigma_f^2) + \sigma_\varepsilon^2], \tag{7}$$

$$E[V_{ewt}] = \sum_{i=1}^{D_t} \left[E[f_d^2] + \frac{1}{N_t^2} \sum_{i=1}^{N_t} E[\varepsilon_{id}^2] \right] = D_t[(\mu_f^2 + \sigma_f^2) + \sigma_\varepsilon^2 / N_t]. \tag{8}$$

To be more concrete, assume (consistent with the descriptive statistics in Table I) that the equal-weighted portfolio of stocks has (annualized) mean and standard deviation of 12 and 20 percent respectively, while the (annualized) standard deviation of idiosyncratic shocks is 50 percent. Substituting the values of the parameters, we get:

$$E[V_t] \times 10^4 = 234 = \underbrace{\text{Systematic}}_{34} + \underbrace{\text{Idiosyncractic}}_{209} \tag{9}$$

$$E[V_{ewt}] \times 10^4 = 34 = \underbrace{\text{Systematic}}_{34} + \underbrace{\text{Idiosyncratic}}_{0}. \tag{10}$$

This decomposition illustrates that the effect of idiosyncratic risk is diversified away in the equal-weighted portfolio variance measure but constitutes almost 85 percent of the average stock variance measure. Our measure, V, is fundamentally a measure of idiosyncratic risk.

It is also instructive to examine the variances of the two variance measures. We have

$$\begin{aligned} \text{Var}[V_t] &= \sum_{i=1}^{D_t} \left[\text{Var}[f_d^2] + \frac{4}{N_t^2} E[f_d^2] \sum_{i=1}^{N_t} E[\varepsilon_{id}^2] + \frac{1}{N_t^2} \sum_{i=1}^{N_t} \text{Var}[\varepsilon_{id}^2] \right] \\ &= \sum_{i=1}^{D_t} [2\sigma_f^2(\mu_f^2 + \sigma_f^2) + 4(\mu_f^2 + \sigma_f^2)\sigma_\varepsilon^2 / N_t + 2\sigma_\varepsilon^4 / N_t], \end{aligned} \tag{11}$$

Table I

Descriptive Statistics of Returns and Volatility Measures

This table presents descriptive statistics on returns and measures of volatility. The sample period is July 1962 to December 1999 (450 monthly observations). The variable r is the typical stock return and r_p is the portfolio return, where $p = ew$ and $p = vw$ stand for the equal- and value-weighted portfolios, respectively. The variable V is the average stock variance, SD is the average stock standard deviation calculated as the square root of V, and V_p and SD_p are the portfolio variance and standard deviation, respectively. The variables, V_p and V, are calculated using daily data corrected for serial correlation, as shown in equations (1) and (2), respectively. Dispersion, S, is calculated as shown in equation (15). "Skew" is the skewness, "Kurt" is the kurtosis, "AR_1" is the first-order autocorrelation, and "$AR_{1:12}$" is the sum of the first 12 autocorrelation coefficients. "ADF" is the Augmented Dickey–Fuller statistic for presence of unit root calculated with an intercept and 12 lags. The critical values for rejection of unit root are −3.4475 and −2.8684 at one percent and five percent levels. The first row in Panel A gives average statistics for all stocks.

Panel A: Univariate Statistics

	Mean	Median	StdDev	Min	Max	Skew	Kurt	AR_1	$AR_{1:12}$	ADF
r	0.0104	−0.0090	0.1646	−0.3612	0.6928	0.9584	7.3933	−0.0289	−0.0862	—
r_{ew}	0.0129	0.0153	0.0556	−0.2708	0.2992	−0.2239	6.4965	0.2180	0.1480	−5.6449
r_{vw}	0.0111	0.0132	0.0436	−0.2249	0.1656	−0.4648	5.4971	0.0448	−0.0528	−5.7363
V	0.0286	0.0245	0.0157	0.0099	0.1226	1.9232	8.7414	0.7999	7.4019	−1.1031
SD	0.1640	0.1564	0.0419	0.0995	0.3501	1.0031	4.4407	0.8426	8.3058	−1.2680
S	0.0269	0.0233	0.0148	0.0088	0.0986	1.6451	6.7305	0.8770	8.5479	−0.7176
V_{ew}	0.0017	0.0009	0.0032	0.0001	0.0515	10.0219	140.2248	0.1449	0.6274	−4.9511
SD_{ew}	0.0356	0.0305	0.0208	0.0105	0.2270	3.1770	22.4899	0.3591	2.1791	−3.8937
V_{vw}	0.0019	0.0012	0.0036	0.0001	0.0671	13.7457	242.8002	0.1707	0.8344	−4.7519
SD_{vw}	0.0386	0.0345	0.0202	0.0089	0.2591	3.8199	35.3703	0.4479	3.0480	−3.7424

Panel B: Cross Correlations

	r	r_{ew}	r_{vw}	V	SD	S	V_{ew}	SD_{ew}	V_{vw}
r_{ew}	0.3506	1							
r_{vw}	0.3012	0.8471	1						
V	0.0333	0.0693	0.0693	1					
SD	0.0369	0.0807	0.0830	0.9848	1				
S	0.0351	0.1367	0.1418	0.9797	0.9755	1			
V_{ew}	−0.1103	−0.2911	−0.3148	0.3794	0.3241	0.1861	1		
SD_{ew}	−0.0903	−0.2136	−0.2515	0.3558	0.3244	0.1849	0.8902	1	
V_{vw}	−0.1331	−0.3124	−0.2817	0.4127	0.3606	0.2439	0.8965	0.7303	1
SD_{vw}	−0.1201	−0.2909	−0.2244	0.4363	0.4225	0.2909	0.7954	0.8317	0.8645

$$\begin{aligned} \mathrm{Var}[V_{ewt}] &= \sum_{i=1}^{D_t} \left[\mathrm{Var}[f_d^2] + \frac{4}{N_t^2} E[f_d^2] \sum_{i=1}^{N_t} E[\varepsilon_{id}^2] + \frac{1}{N_t^3} \sum_{i=1}^{N_t} \mathrm{Var}[\varepsilon_{id}^2] \right] \\ &= \sum_{i=1}^{D_t} [2\sigma_f^2(\mu_f^2 + \sigma_f^2) + 4(\mu_f^2 + \sigma_f^2)\sigma_\varepsilon^2/N_t + 2\sigma_\varepsilon^4/N_t^2]. \end{aligned} \tag{12}$$

Substituting the values of the parameters, we get:

$$\mathrm{Std\,Dev}\,[V_t]\times 10^4 = 48.1 \tag{13}$$

$$\mathrm{Std\,Dev}\,[V_{ewt}]\times 10^4 = 47.9, \tag{14}$$

so that the t-ratio (the mean dividend by the standard deviation) is 5.05 for the average stock variance measure and 0.72 for the market variance measure. Average stock variance, V, is measured more precisely in relation to its mean than is V_{ew}. The source of this increased precision is the low measurement error in the pure idiosyncratic risk component. The precision in the measure V makes it a better variable to use in predictive regressions of the market return.

Alternatively, we can also interpret V as a measure of cross-sectional dispersion of stock returns. Consider the cross-sectional variance of stock returns in month t:

$$S_t = \sum_{d=1}^{D_t} \left[\frac{1}{N_t} \sum_{i=1}^{N_t} (r_{id} - r_{ewd})^2 \right]. \tag{15}$$

This is a measure of heterogeneity across the stocks in the market. It can be easily verified from equations (5) and (6) that $S_t = V_t - V_{ewt}$. Given our calculation above, V is an order of magnitude greater than V_{ew}, and therefore S and V are closely related. Almost by definition, the heterogeneity of stock returns is driven by their idiosyncratic shocks. However, viewing V as a measure of average stock variance (mostly idiosyncratic) or as a measure of cross-sectional dispersion allows us to interpret the predictive regression results under different perspectives as discussed in the introduction.

B. Descriptive Statistics

We compute the risk measures using CRSP data from July of 1962 to December of 1999. This is the same sample period used by CLMX (2001) and corresponds to the availability of daily stock return data in CRSP. Each month, we use all the stocks which have a valid return for that month and a valid market capitalization at the end of the previous month.

Table I gives descriptive statistics on the variance measures and corresponding standard deviations $\left(SD_t = \sqrt{V_t} \text{ and } SD_{pt} = \sqrt{V_{pt}}\right)$. Where there is no scope for confusion, we refer to standard deviation as "volatility." The first row (marked r) in Panel A of Table I gives the moments for a typical stock. These are computed as the average of the moments for all stocks.[9]

[9] Since the trading history is different for each stock, the averages are computed over different periods. This explains why the average return of a typical stock (1.04 percent) is different from the average return on the equal-weighted portfolio (1.29 percent).

The time-series mean of average stock volatility (16.40 percent per month) is more than four times the mean volatility of the equal-weighted portfolio (3.56 percent per month). This indicates that idiosyncratic risk represents a large component of total stock risk. All the measures of volatility show substantial time variation. The "standard deviation" of the volatility of the equal-weighted portfolio is 2.08 percent, the same order of magnitude as its mean. The "standard deviation" (4.19 percent per month) of the average stock volatility is only one fourth of its "mean" (16.40 percent per month). This indicates that the average stock volatility is measured more precisely. This evidence is consistent with the discussion in the previous subsection.

Average stock volatility is persistent, displaying an autoregressive root of 0.84. The average stock volatility is substantially more persistent than the volatility of the equal-weighted portfolio, as measured by either the first-order autocorrelation or the first 12 autocorrelations. This high level of persistence also points to the precision with which average stock risk is measured, since any estimation error makes the series less autocorrelated.

Panel B of Table I shows that the average stock volatility is not much correlated with the equal-weighted (0.324) or value-weighted (0.423) portfolio volatilities. Periods of high idiosyncratic risk are not necessarily the same as periods of high market risk. The equal- and value-weighted portfolio volatilities are highly correlated (0.832) with each other. They are both good measures of market risk. The typical stock return, as well as the equal- and value-weighted portfolios' returns, are negatively contemporaneously correlated with the market volatility, in support of the leverage effect of Black (1976) and Christie (1982). In contrast, the average stock return and the market return are *positively* contemporaneously correlated with average stock volatility.[10] Finally, we note the very high (0.980) correlation between average stock variance, V, and cross-sectional dispersion, S. Given this and the fact that the moments of the time series of V and S are very similar, in the rest of the paper we analyze the variable V only, although all the results reported for V also hold for S.

Figure 1 plots the time series of average stock volatility for our sample. The top panel of this figure plots the raw time series while the bottom panel plots its 12-month moving average. A remarkable feature of this graph (first noted by CLMX (2001)) is that average stock volatility shows a clear upward time trend during this sample period. The figure also plots the NBER recession months as shaded bars. We can see that average stock volatility tends to go up around recessions. Figure 2 gives a graphical illustration of the time series of the equal-weighted and value-weighted portfolios' volatilities. These series do not show any significant trend. Although the market volatility was high in the 1970s and 1980s, it seems to have fallen back to average postwar levels in the 1990s. There is also evidence of countercyclical behavior of the market volatility.

[10] Duffee (1995) also finds a positive contemporaneous relation between individual stock returns and individual stock volatility. He suggests that the difference in sign of the correlations is due to the negative skewness of the market factor and the positive skewness of individual stock returns.

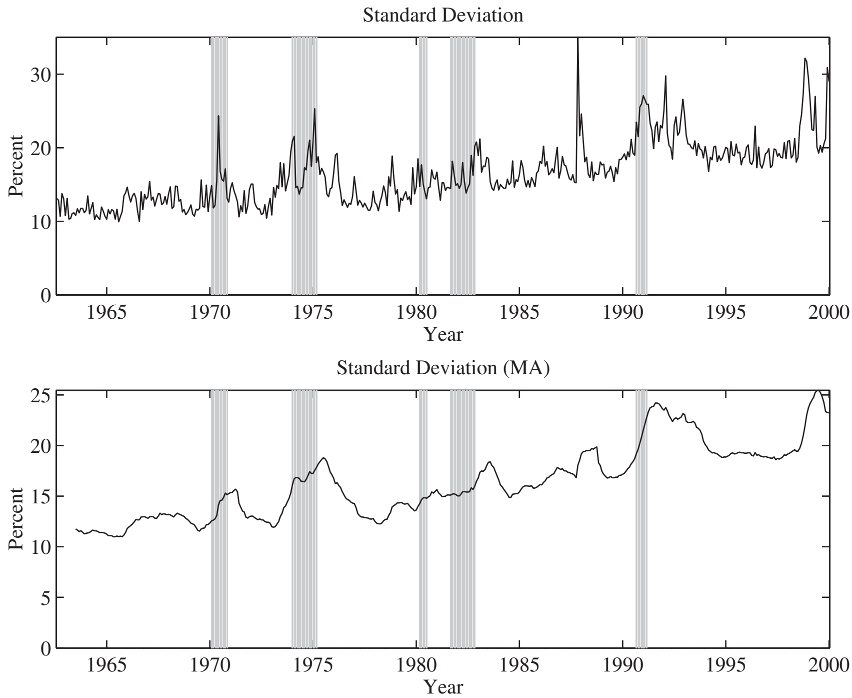

Figure 1. Average stock volatility. This figure plots the average standard deviation of stocks for the period July 1962 to December 1999. Average stock volatility is calculated using daily data from equation (2). The bottom panel uses a 12-month simple moving average of the top panel. NBER recessions are represented by shaded bars.

C. Predictive Regressions

We now explore the linkage between average stock risk and the market return. We regress realized excess returns on the lagged volatility measures. The fitted value of this regression gives the expected return conditional on the lagged volatility.[11] Thus, the forecasting regression is

$$r_{vw,t+1} = \alpha + \beta X_t + \varepsilon_{t+1}, \tag{16}$$

where r_{vw} is the simple (not log) excess return on the market, and X includes different combinations of the market and average stock-risk measures.

Table II presents the results of regressions for the monthly value-weighted market return. The first regression repeats the classic regression of market return on lagged market variance. The extant literature presents conflicting results on the sign of this coefficient. Campbell (1987) and Glosten et al. (1993) find

[11] We use the lagged volatility as a proxy for the expectation of the current period's volatility, which can be justified by the high persistence of the volatility series. The results are essentially the same if we replace volatilities by the fitted values from an ARMA model (see Schwert (1989, 1990b)).

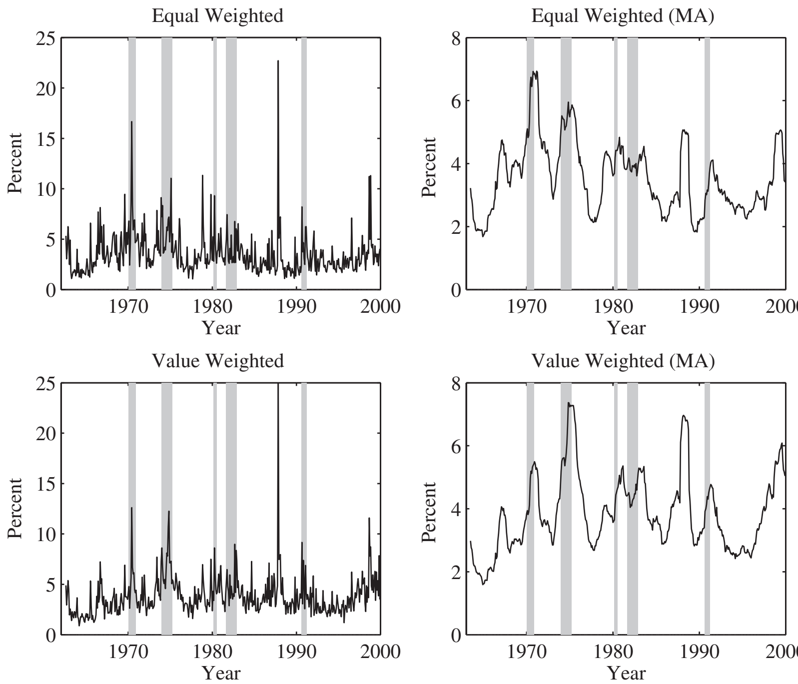

Figure 2. Equal- and value-weighted portfolio volatility. This figure plots the standard deviation for equal- and value-weighted portfolio for the period July 1962 to December 1999. Portfolio volatility is calculated using equation (1). The right two panels use a 12-month simple moving average of the left two panels. NBER recessions are represented by shaded bars.

a significantly negative relation, whereas Campbell and Hentschel (1992) and French et al. (1987) find a significantly positive relation. For our data and sample period, we find a negative but insignificant coefficient.

The second regression shows that the average stock variance is positively significant in predicting market returns. The coefficient has a *t*-statistic above two and the $\bar{R}^2$ of the regression is around one percent.[12] This significance actually increases when we add the market variance as a second regressor. Including both variance measures makes the coefficient on market variance significantly negative and the coefficient on average individual stock variance even more significantly positive. The $\bar{R}^2$ of this regression is as high as two percent.

We test whether the importance of average stock variance derives from it being a predictor of subsequent market variance. We regress market variance on its

[12] To account for the heteroskedasticity and possible autocorrelation in returns, we report only Newey–West corrected *t*-statistics (with six lags). The unadjusted *t*-statistic is 2.36. We also checked the predictive ability of the measure of dispersion, S, introduced in equation (15). The coefficient on lagged S is 0.405 with a *t*-statistic of 3.46.

Table II

Forecasts of Value-Weighted Portfolio Returns

This table presents the results of a one-month-ahead predictive regression of the excess value-weighted portfolio return on lagged explanatory variables. The variable V is the average stock variance, and the variable V_{vw} is the value-weighted volatility; both are calculated using daily data, as shown in equations (1) and (2), respectively. The sample period is August 1963 to December 1999 (437 monthly observations). The first row in each regression is the coefficient and the second row is the Newey–West adjusted t-statistic. The third row of each regression shows the bootstrapped (two-sided) p-value from the distribution generated by 10,000 replications of the bootstrap. See Section II.A for further details on the bootstrap experiment.

		Variance		Standard Deviation		ln Variance		
	$CNST$	V_{vw}	V	SD_{vw}	SD	$\ln(V_{vw})$	$\ln(V)$	$\bar{R}^2$
1.	0.007	−0.597						0.02%
	(3.21)	(−1.07)						
		[0.428]						
2.	−0.004		0.336					
	(0.96)		(2.57)					1.19%
			[0.016]					
3.	−0.005	−1.449	0.478					
	(−1.35)	(−2.70)	(3.86)					2.17%
		[0.051]	[0.000]					
4.	0.006			−0.008				
	(1.25)			(−0.06)				−0.23%
				[0.954]				
5.	−0.016				0.129			
	(−2.04)				(2.88)			1.26%
					[0.007]			
6.	−0.015			−0.144	0.159			1.40%
	(−2.01)			(−0.99)	(3.25)			
				[0.350]	[0.003]			
7.	0.011					0.001		−0.21%
	(0.58)					(0.29)		
						[0.781]		
8.	0.046						0.011	1.18%
	(3.29)						(2.92)	
							[0.005]	
9.	0.038					−0.002	0.012	1.08%
	(1.98)					(−0.70)	(3.00)	
						[0.501]	[0.004]	

lagged value and on the lagged average stock variance. The coefficient on the lagged market variance is 0.161 (t-statistic of 1.92), while the coefficient on lagged average stock variance is only 0.005 (t-statistic of 0.65). We therefore reject this hypothesis.

We also run regressions of market returns on lagged standard deviations and lagged log of variances. One potential problem with the regressions on the variance measures is the nonsphericity of residuals. Table I shows that the times series of the variance measures display large kurtosis and skewness. This can potentially affect the distribution of standard errors. Like Andersen et al. (2001), we find that the square root and log transformations of the variance measures are closer to normally distributed than the variances themselves. As reported in Table I, the standard deviation measures have lower skewness and lower kurtosis than the variance measures. The skewness coefficients of the logs of V and V_{vw} are 0.320 and 0.273, respectively, and the kurtosis coefficients are 2.741 and 3.838, close to those of a normally distributed random variable. Rows 4 to 6 of Table II report the regressions on standard deviations and the last three lines, the regression on logs of variances. With these transformed variables, the relation between market returns and average stock risk remains positive. In contrast, the sign of the coefficient on market risk is not robust to the transformations.

II. Robustness Checks

In this section, we confirm the relation between average stock variance and the return on the market through a battery of robustness checks. We run a bootstrap analysis, extend the sample, and confirm the predictability of market returns with V after controlling for variables proxying for business cycle fluctuations.

A. Correcting Small-Sample Biases

There are two potential sources of small-sample problems that may affect the regressions reported in Table II. First, both the regressand and the regressors display high levels of skewness and kurtosis. Second, the regressors are highly persistent and contemporaneously correlated with the regressand.

We study the impact of these problems on our tests using a bootstrap experiment (see Davison and Hinkley (1997) and Efron and Tibshirani (1993) for an exposition of bootstrap methods). We assume that both the average variance, V, and the market variance, V_{vw}, follow an AR(12) process. Consistent with a prior of no predictability, we assume that market returns are i.i.d. The assumed dynamics under the null hypothesis of our test are then

$$\begin{aligned} r_{vwt+1} &= \mu + \varepsilon_{t+1} \\ V_{t+1} &= \alpha + \sum_{i=0}^{11} \phi_i V_{t-i} + \xi_{t+1} \\ V_{vwt+1} &= \kappa + \sum_{i=0}^{11} \psi_i V_{vwt-i} + \eta_{t+1}. \end{aligned} \tag{17}$$

We allow the innovations to the three variables, ε, ξ, and η, to be contemporaneously correlated and do not impose any particular distributional assumption on them.[13]

The parameter estimates for the VAR in (17) confirm that both the market variance and the average stock variance processes are highly persistent. The autocorrelation in the residuals of the VAR is negligible at all lags, leading us to believe that the VAR captures most of the serial dependence in the variables. The residuals of all three variables are highly skewed and leptokurtic. The correlation between the shocks to V_{vw} and r_{vw} is substantial at -0.310, while the correlation between residuals from V and r_{vw} is negligible at -0.045.[14]

For each replication in the bootstrap, we simulate paths of the variances, V and V_{vw}, and the returns, r_{vw}, by sampling the estimated residuals from the VAR (with replacement) and using them recursively in the system (17). The simulated time series of the variables are then used in regressions of the form (16). We generate an empirical distribution of the Newey–West corrected t-statistic of the coefficient from 10,000 replications of the procedure and compare the t-statistic estimated from the data with the bootstrapped distribution to calculate the p-value. We bootstrap the t-statistics instead of the regression coefficients, as suggested by Efron and Tibshirani (1993), since the distribution of the t-statistic does not depend on any nuisance parameters, such as the variance of the residuals.

The bootstrapped p-values are reported in the third row of each regression in Table II. In regression 1, the p-value from the bootstrap is 0.428, which is much higher than the asymptotic p-value (0.284 for a t-statistic of -1.07). In contrast, the bootstrapped p-value in regression 2 (0.016) is highly significant and is much closer to its asymptotic value (0.010). The coincidence between the bootstrapped and the asymptotic distribution of the t-statistic in this regression is likely due to the low correlation between the innovations to V and the innovations to r_{vw}. Finally, in the third regression, both coefficients are still significant after correcting the small-sample biases. Again, the bootstrapped confidence interval for the t-statistic on the coefficient of V_{vw} is wider than its asymptotic counterpart while there is no such difference for the coefficient on V. Similar results hold when we use the standard deviations and logs of variances as our regressors. We conclude that the relation between market return and average stock risk is not a small-sample illusion.

[13] Ferson, Sarkissian, and Simin (2001) show that time-varying and persistent expected returns (instead of the constant μ of our null) might lead to a spuriously high t-statistic on a persistent regressor that is actually independent of expected returns. Unfortunately, it is difficult to correct for this potential problem since we do not have a good model of time-varying expected returns.

[14] These correlations are between the residuals of our VAR(12) specification. Stambaugh's (1999) specification involves an AR(1) process for the regressor and a one-period ahead predictive regression for the excess returns. Using that specification in our problem, the correlations are -0.289 for innovations between returns and market variance, and -0.022 for innovations between returns and average stock variance. Note that the results of Cavanagh, Elliott, and Stock (1995) and Elliott and Stock (1994) show that the asymptotic distribution of the t-statistics is still valid in predictive regressions when regressors have a (near) unit root, provided that the correlation between the innovations to the regressor and the regressand is zero. This is roughly the case when we use average stock variance as a regressor.

B. Extending the Sample

The sample used above starts in July of 1962 because of daily data availability in the CRSP. We compute an alternative measure of average stock variance as the average across all stocks of their monthly returns demeaned by subtracting the square of the average stock return in that month (ignoring the adjustment for the squared mean return does not change any of our results):

$$V_t^{lf} = \frac{1}{N_t}\sum_{i=1}^{N_t} r_{it}^2 - r_{ewt}^2. \tag{18}$$

The superscript *lf* stands for "low frequency," in contrast to the measure of equation (2) which uses high-frequency (daily) data. Since the low-frequency measure requires only monthly return data on individual stocks, we are able to compute the average stock variance since the beginning of the CRSP tapes in January of 1926. To construct a time series of market variance for the longer sample, we splice together two series. For the sample period of July of 1962 to December of 1999, we use CRSP daily value-weighted returns as before and for the earlier part of the sample we use daily data from Schwert (1990a).

Table III presents descriptive statistics on the low-frequency measure. Average stock volatility in the longer sample is slightly lower and has somewhat higher skewness and kurtosis than that in the shorter sample. Panel B shows that the averages of both the low-frequency and the high-frequency measures of volatility are very close to each other in their common sample. However, the "standard

Table III

Low-Frequency Measures of Variance

This table presents descriptive statistics on the low-frequency measures of variance. The low-frequency measure of average stock variance is computed from equation (18). The high-frequency average stock variance, shown for comparison, is computed from equation (2). "Skew." is the skewness, "Kurt." is the kurtosis, "AR_1" is the first-order autocorrelation, and "$AR_{1:12}$" is the sum of the first 12 autocorrelation coefficients. "ADF" is the Augmented Dickey–Fuller statistic for presence of unit root calculated with an intercept and 12 lags. The critical values for rejection of unit root are −3.4475 and −2.8684 at one percent and five percent levels. Panel B also reports the cross correlation between the two measures.

	Mean	Median	Std.Dev.	Min.	Max.	Skew.	Kurt.	AR_1	$AR_{1:12}$	ADF
Panel A: Descriptives (Sample January 1926 to December 1999)										
V^{lf}	0.0246	0.0164	0.0471	0.0022	0.7720	10.6461	144.8416	0.4604	2.5886	−4.1489
SD^{lf}	0.1384	0.1280	0.0741	0.0474	0.8786	3.9099	31.3835	0.5955	5.1557	−3.0091
Panel B: Comparison with High-Frequency Measures (Sample July 1962 to December 1999)										
V^{lf}	0.0257	0.0210	0.0206	0.0055	0.2461	4.7815	40.5841	0.3793	3.0857	−1.8878
V	0.0286	0.0245	0.0157	0.0099	0.1226	1.9232	8.7414	0.7999	7.4019	−1.1031
SD^{lf}	0.1528	0.1450	0.0490	0.0743	0.4961	1.9498	11.0519	0.5341	4.6606	−1.8620
SD	0.1640	0.1564	0.0419	0.0995	0.3501	1.0031	4.4407	0.8426	8.3058	−1.2680
$\text{Corr}(V^{lf}, V) = 0.7475$, $\text{Corr}(SD^{lf}, SD) = 0.8166$										

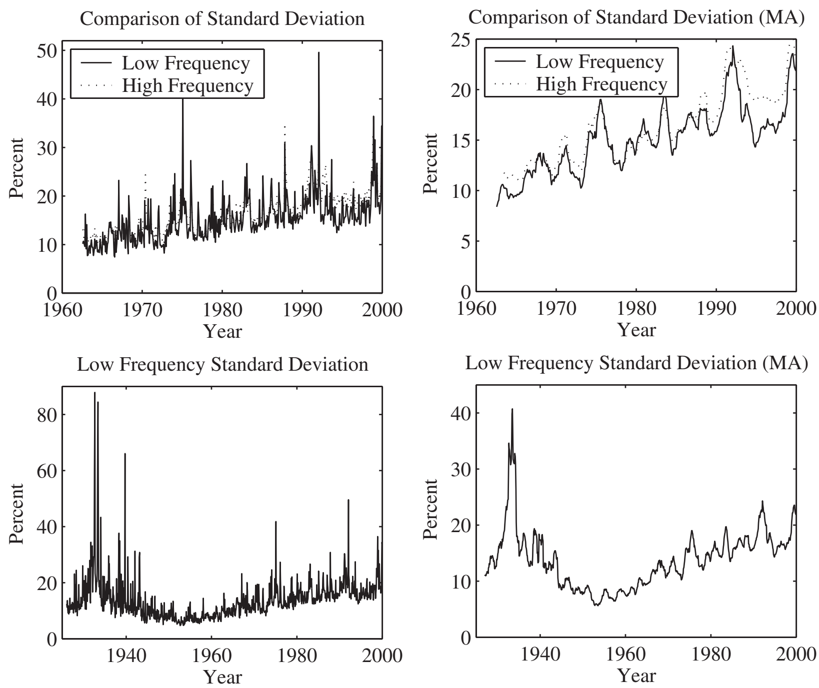

Figure 3. Average low-frequency stock volatility. This figure plots the average cross-sectional stock standard deviation of stocks calculated using low frequency monthly data from equation (18). The top two panels compare low-frequency estimates (solid line) against the high-frequency measure (dotted line) for the sample period July 1962 to December 1999. The bottom two panels plot the raw time series for low-frequency standard deviation of stocks for the sample period January 1926 to December 1999. The right two panels use a 12-month simple moving average of the left two panels.

deviation" of the low-frequency measure is higher than that of the high-frequency measure (use of a single monthly return squared is a very noisy measure of that stock's variance, although part of the noise cancels out when we average across a large number of stocks). Despite this, both high- and low-frequency measures of volatility are highly correlated, with a coefficient of 0.817. The top two panels of Figure 3 further illustrate the close correspondence between the two measures of volatility in their common sample. The bottom two panels of this figure show the time series of the low-frequency measure since 1926. It can be seen that average volatility was very high in the prewar period and that the upward trend in volatility mentioned in Subsection I.B (and noted by CLMX (2001)) is a phenomenon only since the 1960s.

Panel A of Table IV presents the regression results for the shorter sample period to facilitate comparison with the results of Table II. The lagged average stock variance is again significantly positive in explaining the value-weighted market returns. The t-statistic (2.16) is somewhat lower than that in Table II (2.57) because the low-frequency measure is noisier, which creates an errors-in-variables pro-

Table IV

Forecasts of Value-Weighted Portfolio Returns Based on a Low-Frequency Measure of Average Volatility

This table presents the results of a one-month-ahead predictive regression of the excess value-weighted portfolio returns on lagged explanatory variables for a longer sample and for a different measure of average volatility. The variable V^{lf} is the low-frequency measure of average stock variance, calculated using monthly data according to equation (18). The variable V_{vw} is the value-weighted volatility, calculated using CRSP daily data for the sample period July 1962 to December 1999 and using Schwert's daily data for the earlier sample period. The sample period is August 1963 to December 1999 (437 monthly observations) in Panel A and February 1928 to December 1999 (863 monthly observations) in Panel B. The first row in each regression is the coefficient, the second row is the Newey–West adjusted t-statistic, and the third row is the bootstrapped p-value. The bootstrap experiment uses 10,000 replications and is carried out under the null of no predictability of returns.

	CNST	V_{vw}	V^{lf}	$\bar{R}^2$
Panel A: Sample August 1963 to December 1999				
1.	0.007	−0.597		0.02%
	(3.21)	(−1.07)		
		[0.418]		
2.	−0.000		0.258	0.79%
	(−0.06)		(2.16)	
			[0.043]	
3.	0.001	−0.666	0.266	0.86%
	(0.26)	(−1.30)	(2.15)	
		[0.339]	[0.044]	
Panel B: Sample February 1928 to December 1999				
1.	0.005	0.606		0.37%
	(2.03)	(0.69)		
		[0.514]		
2.	0.002		0.262	1.41%
	(0.81)		(2.27)	
			[0.036]	
3.	0.002	0.252	0.240	1.37%
	(0.58)	(0.31)	(2.60)	
		[0.768]	[0.015]	

blem. Similarly, in the common sample, the coefficient of the low-frequency measure (0.258) is lower than the coefficient of the high-frequency measure (0.336) due to the downward bias induced by errors in variables. The bootstrap tests indicate that average variance is still significant at the 95 percent confidence level.

For the longer sample, we find that average stock variance is even more highly positively significant in forecasting the market's return. The estimated coefficient on average stock variance is 0.262 and the corresponding t-statistic is 2.27 (bootstrapped p-value of 0.036). The value-weighted market variance remains insignificant, although with a coefficient that is now positive. Given the likely downward bias in the coefficient and t-statistics, the results in Table IV are impressive.[15] Finally, the last regression in Panel B shows that the effect of average stock variance becomes even stronger after the inclusion of market variance as an additional regressor. These regressions confirm that our earlier results are not an artifact of a particular definition of average stock variance or of a particular sample period.

C. Controlling for the Business Cycle

One potential explanation for our finding is that average stock variance proxies for business cycle fluctuations. Indeed, CLMX (2001) have found, and our Figure 1 illustrates, that average stock variance is countercyclical. At the same time, Chen, Roll, and Ross (1986), Keim and Stambaugh (1986), Campbell and Shiller (1988), Fama and French (1988, 1989), Fama (1990), Campbell (1991), and Ferson and Harvey (1991) find evidence that the stock market can be predicted by variables related to the business cycle, such as the dividend–price ratio, the relative Treasury bill rate, the term spread, and the default spread. To test this "proxy" hypothesis, we examine the relation between the stock market returns and the average stock variance using macro variables as controls for business cycle fluctuations.

The dividend–price ratio is calculated as the difference between the log of the last 12 month dividends and the log of the current level of the CRSP value-weighted index. The three-month Treasury bill rate is obtained from Ibbotson Associates. The relative Treasury bill stochastically detrends the raw series by taking the difference between the Treasury bill rate and its 12-month moving average. The term spread is calculated as the difference between the yield on long-term government bonds and the Treasury bill rate, also obtained from Ibbotson Associates. The default spread is calculated as the difference between the yield on BAA- and AAA-rated corporate bonds, obtained from the FRED database. As a final variable, we include the lagged return on the market to control for the serial correlation in returns that might spuriously affect the predictability results.[16]

In the regressions with control variables, we again use a bootstrap experiment to calculate p-values. We still impose a null of no predictability in the market returns and assume that both the average variance, V, and the market variance, V_{vw},

[15] If we assume that the lower coefficient on V^{lf} than on V in the common sample is entirely due to the errors-in-variables bias, we see that the coefficient in the regression using V^{lf} is less than 77 percent ($0.768 = 0.258/0.336$) of what it would be in the absence of measurement error. Similarly, the errors-in-variables problem makes the t-statistic only 84 percent ($0.84 = 2.16/2.57$) of what it would be absent that problem. If we use these attenuation ratios in the longer sample, we obtain new estimates of $0.262/0.768 = 0.341$ and $2.27/0.84 = 2.70$, respectively. These are estimates of the coefficient and the t-statistic we would obtain if we could have used the high-frequency variance measure (with its lower measurement error) in the sample since 1928. This is of course an imperfect adjustment, but it helps make the coefficients and t-statistics of the regressions using V and V^{lf} comparable.

[16] Alternatively, Lewellen (2001) suggests using the lagged 12-month return as a correction for the mean reversion in the stock market. The results do not change with this alternative correction.

follow AR(12) processes. Now, we let the vector of business cycle variables Z_t follow a VAR(12) process. The assumed dynamics under the null hypothesis of our test are then

$$\begin{aligned} r_{vwt+1} &= \mu + \varepsilon_{t+1} \\ V_{t+1} &= \alpha + \sum_{i=0}^{11} \phi_i V_{t-i} + \xi_{t+1} \\ V_{vwt+1} &= \kappa + \sum_{i=0}^{11} \psi_i V_{vwt-i} + \eta_{t+1} \\ Z_{t+1} &= \lambda + \sum_{i=0}^{11} \pi_i Z_{t-i} + \nu_{t+1}, \end{aligned} \tag{19}$$

where λ is a vector and π_i are matrices of coefficients. We again conduct the bootstrap experiment by jointly sampling from the innovations ε, ξ, η, and ν.

Table V examines the forecasts of the market return controlling for the business cycle. In general, the predictability of the market by the control variables is in line with previous research. The dividend–price ratio is not significant for explaining returns. This is partly explained by previous research that shows that dividend–yield predictability is significant only at longer forecasting horizons and by the inclusion of the 1990s in our sample period. This is consistent with the evidence in Goyal and Welch (2002). The relative Treasury bill rate is strongly significant with a negative coefficient in our sample. Both the term spread and the default spread are strongly significant in explaining returns.

When we include the volatility measures along with the control variables in the regression, the findings of Table II hold up. The coefficient on market variance is insignificantly negative[17] and the coefficient on average stock variance is significantly positive. The magnitude of the coefficient is similar to that reported in Table II, which indicates that the effect of average stock variance is largely orthogonal to the control variables. The $\bar{R}^2$ of the regressions goes up by as much as five percent when the volatility measures are added to the regression with control variables.

Table VI repeats this exercise with the low-frequency measure of volatility. Panel A reports the results for the sample period of 1963 to 1999 and can be directly compared with the previous Table V. The coefficient of the average stock variance is again positive (0.219), albeit with an insignificant t-statistic (1.58). This insignificance is undoubtedly explained by the errors-in-variables problem caused by the

[17] We should not interpret our results on the insignificance of the market variance as a predictor of the market's return as a rejection of the ICAPM. The ICAPM postulates a positive *partial* relation between the market's return and its variance, after taking into account the covariance with all other state variables. To the extent that we do not control for the covariance of the market with all the other state variables, we cannot use our results as evidence against the ICAPM. Scruggs (1998) uses the covariance between excess returns on long bonds and the market return and finds a significant (positive) partial relation between risk and return in the market in support of the ICAPM. Our results are fully compatible with this.

Table V

Forecasts of Value-Weighted Portfolio Returns Controlling for Business Cycle Variables

This table presents the results of a one-month-ahead predictive regression of excess value-weighted portfolio returns on lagged explanatory variables. The variable V is the average stock variance, V_{vw} is the value-weighted volatility, and r_{vw} is the value-weighted portfolio return in excess of the 3 month T-bill rate. The variables, V and V_{vw}, are calculated using daily data. *DP* is the logged dividend price ratio calculated as the difference between the log of last 12 month dividends and the log of the current price index of the CRSP value-weighted index. *RTB* is the relative three-month Treasury bill rate calculated as the difference between T-bill and its 12-month moving average. *Term Spread* is the difference between the yield on long-term government bonds and T-bill. *Default Spread* is the difference between the yield on BAA- and AAA-rated corporate bonds. The sample period is August 1963 to December 1999 (437 monthly observations). The first row in each regression is the coefficient, the second row is the Newey–West adjusted t-statistic, and the third row is the bootstrapped p-value. The bootstrap experiment uses 10,000 replications and is carried out under the null of no predictability of returns.

	CNST	V_{vw}	V	r_{vw}	*DP*	*RTB*	*Term Spread*	*Default Spread*	$\bar{R}^2$
1.	0.012			−0.008	−0.000	−7.142	−0.322	1.586	4.00%
	(0.35)			(−0.13)	(−0.03)	(−3.05)	(−2.35)	(2.26)	
				[0.860]	[0.960]	[0.000]	[0.020]	[0.020]	
2.	0.012	−0.958		−0.035	−0.001	−7.545	−0.327	1.714	4.34%
	(0.33)	(−1.96)		(−0.70)	(−0.09)	(−2.94)	(−2.36)	(2.40)	
		[0.150]		[0.500]	[0.900]	[0.000]	[0.020]	[0.020]	
3.	0.047		0.363	−0.004	0.010	−5.617	−0.440	1.648	4.92%
	(1.28)		(2.20)	(−0.07)	(1.14)	(−2.26)	(−3.03)	(2.37)	
			[0.030]	[0.920]	[0.300]	[0.010]	[0.000]	[0.020]	
4.	0.074	−2.230	0.665	−0.065	0.018	−5.285	−0.553	1.997	6.97%
	(1.81)	(−4.93)	(4.06)	(−1.35)	(1.74)	(−2.06)	(−3.56)	(2.79)	
		[0.000]	[0.000]	[0.230]	[0.130]	[0.020]	[0.000]	[0.010]	

measurement noise in V^{lf}. For the full sample, the coefficient on V^{lf} is 0.214, with a t-statistic of 1.86.[18] The impact of the market variance is negative in the shorter sample and positive in the longer sample but insignificant in both samples (the bootstrapped p-value of the market variance in regression 4 of Panel A is more than five percent). We conclude that the relation between market return and total stock risk is robust to controlling for additional predictors of the stock market.

III. Economic Significance

In this section, we explore the economic significance of the predictability results. We simulate the returns of a trading strategy based on "out-of-sample," step-ahead

[18] The attenuation ratios in the coefficient and the t-statistic are 0.219/0.363 = 0.603 and 1.58/2.20 = 0.72, respectively, for the short sample. Using these adjustments, the corrected coefficient would be 0.214/0.603 = 0.355 and the corrected t-statistic would be 1.86/0.72 = 2.58 in the long sample. Similarly, the attenuation corrected coefficient and t-statistic of the average stock variance for the long sample in regression 4 are 0.485 and 4.64, respectively.

Table VI

Forecasts of Value-Weighted Portfolio Returns Based on Low-Frequency Measure of Average Volatility Controlling for Business Cycle

This table presents the results of a one-month-ahead predictive regression of excess value-weighted portfolio returns on lagged explanatory variables for a longer sample and for a different measure of average volatility. The variable V^{lf} is the average stock variance, calculated using cross-sectional monthly data. The variable V_{vw} is the value-weighted volatility, calculated using CRSP daily data for the sample period July 1962 to December 1999 and using Schwert's daily data for the earlier sample period. The variable r_{vw} is the value-weighted portfolio return in excess of the three-month T-bill rate. *DP* is the logged dividend price ratio calculated as the difference between the log of last 12 month dividends and the log of the current price index of the CRSP value-weighted index. *RTB* is the relative three-month Treasury bill rate calculated as the difference between T-bill and its 12-month moving average. *Term Spread* is the difference between the yield on long-term government bonds and T-bill. *Default Spread* is the difference between the yield on BAA- and AAA-rated corporate bonds. The sample period is August 1963 to December 1999 (437 monthly observations) in Panel A and February 1928 to December 1999 (863 monthly observations) in Panel B. The first row in each regression is the coefficient, the second row is the Newey–West adjusted t-statistic, and the third row is the bootstrapped p-value. The bootstrap experiment uses 10,000 replications and is carried out under the null of no predictability of returns.

	CNST	V_{vw}	V^{lf}	r_{vw}	*DP*	*RTB*	*Term Spread*	*Default Spread*	$\bar{R}^2$
	Panel A: Sample August 1963 to December 1999								
1.	0.012			−0.008	−0.000	−7.142	−0.322	1.586	4.00%
	(0.35)			(−0.13)	(−0.03)	(−3.05)	(−2.35)	(2.26)	
				[0.896]	[0.973]	[0.006]	[0.027]	[0.035]	
2.	0.012	−0.958		−0.035	−0.001	−7.545	−0.327	1.714	4.34%
	(0.33)	(−1.96)		(−0.70)	(−0.09)	(−2.94)	(−2.36)	(2.40)	
		[0.168]		[0.493]	[0.929]	[0.007]	[0.024]	[0.025]	
3.	0.030		0.219	−0.025	0.005	−6.437	−0.386	1.569	4.32%
	(0.82)		(1.58)	(−0.44)	(0.54)	(−2.70)	(−2.71)	(2.25)	
			[0.149]	[0.671]	[0.610]	[0.013]	[0.010]	[0.033]	
4.	0.032	−1.081	0.247	−0.058	0.005	−6.799	−0.401	1.711	4.81%
	(0.85)	(−2.37)	(1.60)	(−1.18)	(0.54)	(−2.65)	(−2.74)	(2.41)	
		[0.105]	[0.154]	[0.250]	[0.615]	[0.014]	[0.010]	[0.027]	
	Panel B: Sample February 1928 to December 1999								
1.	0.014			0.103	0.003	−5.270	−0.053	0.314	1.66%
	(0.84)			(1.58)	(0.57)	(−1.87)	(−0.80)	(0.52)	
				[0.122]	[0.582]	[0.077]	[0.448]	[0.627]	
2.	0.016	0.635		0.114	0.003	−5.318	−0.029	0.015	1.92%
	(1.04)	(0.68)		(1.67)	(0.74)	(−1.97)	(−0.41)	(0.03)	
		[0.528]		[0.108]	[0.478]	[0.062]	[0.699]	[0.979]	
3.	0.027		0.214	0.067	0.006	−5.201	−0.071	−0.039	2.21%
	(1.58)		(1.86)	(1.06)	(1.32)	(−1.87)	(−1.06)	(−0.06)	
			[0.085]	[0.313]	[0.206]	[0.074]	[0.318]	[0.950]	
4.	0.027	0.380	0.180	0.079	0.006	−5.241	−0.054	−0.162	2.22%
	(1.51)	(0.41)	(1.81)	(1.14)	(1.26)	(−1.94)	(−0.77)	(−0.26)	
		[0.708]	[0.098]	[0.262]	[0.227]	[0.067]	[0.454]	[0.808]	

forecasts of the market using the volatility measures.[19] The trading strategy is similar to that of Breen, Glosten, and Jagannathan (1989).

Although the sample period starts in July of 1962, the forecasting exercise starts only in July of 1967, to allow for 60 months of data in the estimation of the first set of parameters. After that date, we use an expanding window to reflect the real-time nature of the problem. Thus, for each month T after July of 1967, we estimate the forecasting regression

$$r_{vwt+1} = \alpha + \beta X_t + \varepsilon_t, \quad t = 1, \ldots, T-1, \tag{20}$$

using all the data available up to time T. The regressors X include different sets of the forecasting variables. The estimated α and β coefficients are then used to forecast the market return at time $T+1$ as $\hat{r}_{vwT+1} = \hat{\alpha} + \hat{\beta} X_T$. At time T, the strategy invests 100 percent in the stock index if the forecasted excess return of stocks over the risk-free rate is greater than zero; otherwise it invests 100 percent in Treasury bills. At time $T+1$, the return of the portfolio is realized, a new regression is estimated, a return forecast computed, and new portfolio weights determined. In this way, we obtain a time series of returns to the trading strategy.

To translate the returns into a measure of investors' welfare, we assume a quadratic utility investor with relative risk aversion of γ. The investor's utility at time $t+1$ is given by

$$U(W_{t+1}) = W_t\left(R_{t+1} - \frac{\gamma}{2(\gamma+1)} R_{t+1}^2\right), \tag{21}$$

where R is the gross return on the trading strategy.[20] To compare the expected utility of the trading strategy with simply buying and holding the market, we follow Fleming, Kirby, and Ostdiek (2001) and assume that the investor is willing to pay a constant fee Δ per period to a manager that implements the trading strategy. In other words, the fee is determined by the equation:

$$\sum_{t=1}^{T}\left[R_{vwt} - \frac{\gamma}{2(\gamma+1)} R_{vw,t}^2\right] = \sum_{t=1}^{T}\left[R_t - \Delta - \frac{\gamma}{2(\gamma+1)}(R_t - \Delta)^2\right]. \tag{22}$$

The results from this trading strategy are given in Table VII. We choose five different sets of conditioning variables, X_t, for the exercise. The first three regressions correspond to the three rows of Table II and the fourth and fifth regressions correspond to rows 1 and 4, respectively, in Table V. For all strategies, we present the

[19] The experiment we describe is not truly out of sample since we have used the entire sample to uncover the predictive ability of average stock variance.

[20] The quadratic utility function is $U(W) = W - \frac{a}{2}W^2$. This implies that the relative risk aversion coefficient is given by $\gamma = \frac{aW}{1-aW}$. We can rewrite this as $aW = \frac{\gamma}{1+\gamma}$. Now reconsider the utility function:

$$U(W_{t+1}) = W_{t+1} - \frac{a}{2}W_{t+1}^2 = W_t R_{t+1} - \frac{a}{2}W_t^2 R_{t+1}^2$$

$$= W_t\left[R_{t+1} - \frac{a}{2}W_t R_{t+1}^2\right] = W_t\left[R_{t+1} - \frac{\gamma}{2(1+\gamma)} R_{t+1}^2\right].$$

Table VII

Trading Strategy Based on Return Forecasts

This table presents descriptive statistics of a trading strategy based on out-of-sample forecasts of the value-weighted market return. At time t, the trading strategy invests all in the stock index if the forecasted excess return of stocks over the risk-free rate is greater than zero; otherwise it invests all in Treasury bills. The forecasts are based on a regression using all the available data up to time t. The sample period is July 1962 to December 1999; however, the forecasting exercise starts only in July 1967, to allow for 60 months in the estimation of the first forecasting regression. The parameters are then reestimated every month. The mean and standard deviation are annualized. The number of months the trading strategy is invested in the market portfolio is denoted by N. In Panel B, we report the annualized fees that a quadratic utility investor with relative risk aversion γ would be willing to pay a money manager that uses the strategy and still attain the same level of utility as buying and holding the market portfolio.

Panel A: Descriptives

Forecasting Criterion	Mean	Std. Dev.	N
Market buy-hold	0.0666	0.1572	390
V_{vw}	0.0629	0.4257	374
V	0.0712	0.1459	371
V_{vw} and V	0.0645	0.1477	372
Macro	0.0625	0.0854	106
V_{vw}, V, and Macro	0.0564	0.1032	157

Panel B: Annual Fees

	γ		
Forecasting Criterion	1	5	10
V_{vw}	– 0.25%	– 0.25%	– 0.24%
V	0.60%	0.60%	0.62%
V_{vw} and V	– 0.09%	– 0.09%	– 0.08%
Macro	0.32%	0.32%	0.38%
V_{vw}, V, and Macro	– 0.44%	– 0.44%	– 0.38%

annualized mean and the standard deviation of returns. We also report the number of months the trading strategy invests in the market portfolio. We report the fees in annualized terms in Panel B of Table VII for three different values of γ.

The first row in Panel A gives the results of the strategy which simply holds the market portfolio. For our sample period, the market portfolio had an excess return of 6.66 percent with a standard deviation of 15.72 percent annually. Use of the value-weighted market variance as a forecaster results in a slight deterioration of the mean (to 6.29 percent) but also in a marginal reduction in the standard deviation (to 14.77 percent). When we use the average stock variance, we not only get a higher mean (7.12 percent) but also a lower standard deviation (14.59 percent). The use of both the average stock variance and the market variance as signals results in only a slight improvement of the mean return over the trading strategy that uses market variance alone. When we use the macro variables, the market variance, and the average stock variance, we get a much lower mean (5.64 percent) but also a substantial reduction in the standard deviation (10.32 percent).

Even for modest levels of risk aversion, the investor is willing to pay a fee of 60 basis points annually to invest in the strategy that forecasts the market based on the average stock variance. The fee increases with risk aversion. Also, note that although the in-sample $\bar{R}^2$ of regression 4 of Table V is the highest of all the combinations of conditioning variables that we consider in this section, the performance of the corresponding strategy is the worst among all the trading strategies. This reflects the poor out-of-sample performance of the macro variables to forecast stock returns and raises the possibility that the high $\bar{R}^2$ found in Table V may be due to in-sample overfitting or spurious regression.

As an additional check, we employ the Henriksson and Merton (1981) measure of market timing information on the five trading strategies. This is a nonparametric test of whether a set of variables can forecast the direction (not the magnitude) of the market in the next period. Out of the five sets of variables we test, only two were found to be significant for timing the market. The t-statistic for V as a single forecaster is 2.64, and the t-statistic for the set of macro variables (without volatility measures) is 2.94. The nonparametric nature of this test adds robustness to the economic significance of average stock variance as a predictor of the market return. We conclude that not only is the relation between market return and total risk robust out of sample, but also that conditioning on average stock risk can bring substantial economic benefits to investors.

IV. Conclusion

In this paper, we document a link between idiosyncratic equity risk and returns in the stock market. Consistent with some previous studies, we find that the lagged variance of the market has no forecasting power for the market return. However, we do find a significant positive relation between lagged average stock variance and the return on the market. We confirm these results with a variety of robustness checks. We also find that conditioning on average stock risk can bring substantial economic benefits to investors.

We discuss three possible explanations for the predictability of market returns with average stock variance. First, we argue that average stock variance may proxy for background risk, and affect the risk aversion of investors towards traded assets. Second, we point out that our findings are consistent with models based on investor heterogeneity. Third, we discuss that viewing the capital structure of companies from an option perspective would make stocks gain at the expense of bonds when average variance increases. Disentangling the relative merits of these explanations will be the subject of future research.

Appendix: Additional Robustness Checks

Volatility and Liquidity

One concern is that the measure of variance may be proxying for liquidity risk. In fact, Karpoff (1987), Schwert (1989), and Lamoureux and Lastrapes (1990) show that volatility is correlated with volume. In parallel, Chordia, Roll, and Subrahmanyam (2001) and Pastor and Stambaugh (2002) show that variables that proxy for liquidity help explain the cross section of stock returns. This evidence raises the possibility that those variables may also forecast the market return. To investigate whether average stock variance proxies for liquidity, we compute the correlation of V with the proprietary liquidity variables of Chordia et al., -0.081 (not significant), and Pàstor and Stambaugh, -0.137 (not significant), as well as the monthly share turnover on the NYSE, 0.688 (significant). Given the insignificant correlation with the first two liquidity variables, the only remaining cause for concern is the correlation between average stock variance and NYSE turnover. However, this high correlation does not necessarily mean that V is proxying for turnover in forecasting market returns. To assess whether it does, we run predictive regressions of the market return on lagged V and turnover. We find that turnover by itself does not predict the market return. The regression coefficient is insignificant (bootstrapped p-value of 0.099) and the $\bar{R}^2$ is only one half of one percent. When we include both the average variance measure and turnover, the coefficient on the variance is almost unchanged from Table II and retains its significance, while the coefficient on turnover is close to zero (bootstrapped p-value of 0.888). We conclude that the relation between average stock variance and the market return is not a liquidity effect.

Long-Horizon Predictability

Following Fama and French (1988), we examine the long-horizon forecastability of the market return based on average stock variance. The basic intuition is that if returns are predictable by a slow-moving variable, then predictability builds up with the horizon. This is likely to be the case of V, which we have shown to be highly persistent. We cumulate returns over a K-month period and regress them on V at the beginning of the period. For convenience, we use log returns, which makes compounding easier. The regressions we run are

$$\sum_{k=1}^{K} \log\left(1 + r_{vwt+k}\right) = \alpha_K + \beta_K V_t + \varepsilon_{t+1,K}, \;\; K = 1, \ldots, 12. \tag{A1}$$

As is well known, we need to correct the distribution of t-statistics in regressions with overlapping observations. To do so, we use the bootstrap experiment recommended by Hodrick (1992) and Goetzmann and Jorion (1995). We use the data-generating process described in Section II.A to simulate bootstrapped sample paths of market returns and average stock variance. For each sample, we estimate the regression (A1) and compute the t-statistic. We generate the empirical distribution of the t-statistics from 10,000 bootstrapped draws. Table AI reports the results for this experiment. The bootstrapped p-values decrease up to the 12-month horizon and then increase to about five percent at the five-year horizon. The $\bar{R}^2$ increases with K, reaching almost 30 percent at the five-year horizon (although the $\bar{R}^2$ in regressions with overlapping data is artificially inflated by the serial correlation in the residuals). As a final check of long-horizon predictability, we regress nonoverlapping 12-month returns on V. The estimated coeffi-

Table AI
Long-Horizon Regressions

This table presents the results of a K-month-ahead predictive regression of excess value-weighted portfolio log returns on lagged average stock variance, *V*, calculated using daily data. The regression specification is given in equation (A1). The *t*-statistic is the Newey–West adjusted and the *p*-value is calculated from a bootstrap. The bootstrap experiment uses 10,000 replications and is carried out under the null of no predictability of returns. The sample period is August 1963 to December 1999.

K	β	*t-statistic*	*p-value*	$\bar{R}^2$
1	0.327	2.52	0.017	1.11%
3	1.047	4.08	0.001	3.90%
6	1.655	4.03	0.002	5.03%
12	2.561	4.26	0.008	6.19%
24	5.110	4.08	0.051	12.24%
60	11.457	5.89	0.058	29.50%

cient is 2.121, with a *t*-statistic of 2.46, and an $\bar{R}^2$ of 4.04 percent. Unfortunately, we cannot pursue this exercise for longer horizons because the number of nonoverlapping observations decreases rapidly—already for a 12-month horizon, we only have 36 observations. These results confirm that the market predictability based on average variance builds up with the investment horizon.

Impact of Outliers

To address any concern that the results are driven by outliers, such as the extremely negative returns observed during the 1930s, we run quantile regressions and find that the significance of V as a forecaster of the market return comes mainly from quantiles 30 to 90. The minimum absolute deviation (which corresponds to the 50th quantile) estimate of the slope coefficient is 0.451 with a *p*-value of 0.000, which is actually lower than the *p*-value of the OLS estimate, further illustrating the robustness of the relation.

Log Returns

If the returns are log-normally distributed, then the mean of simple returns has a variance component in it. This might create a mechanical relation between returns and variance. To address this concern, we have tried using log returns instead of simple returns in the predictive regressions. The results are essentially unchanged for all measures of volatility and sample periods.

January Effect

The January effect of Keim (1983) and Reinganum (1983) is a well-known anomaly of stock returns. We examine whether it affects our results by including a dummy for January in the predictive regressions. We find that the dummy is only marginally significant and does not change the regression coefficients of V at all.

Other Subsamples

To address the concern that our results are being driven either by the good performance of the market in the 1990s or by the secular increase in volatility from 1962 to 1999, we examine additional subsamples. The first subsample goes from 1962 to 1990, while the second one goes from 1926 to 1961. We again run regressions of the market return on the lagged measures of average stock variance and market variance. The coefficient on the market variance is significantly negative in the first subsample and insignificantly positive in the second. The coefficient on average stock variance is positive in both subsamples, with bootstrapped p-values of 0.035 and 0.034, respectively, in the two sample periods.

Residuals from Fama–French Three-Factor Model

We construct measures of pure idiosyncratic risk using residuals from the Fama–French (FF) three-factor model.[21] Using the FF model, we construct a measure of idiosyncratic risk as follows:

$$r_{it} = \alpha + \beta_{i1}\,\mathrm{SMB}_t + \beta_{i2}\,\mathrm{HML}_t + \beta_{i3}\,\mathrm{MKT}_t + \varepsilon_{it}^{FF} \tag{A2}$$

$$V_t^{FF} = \frac{1}{N_t}\sum_{i=1}^{N_t}\left(\varepsilon_{it}^{FF}\right)^2. \tag{A3}$$

Note that V^{FF} is a *low-frequency* estimator of idiosyncratic variance. Over the sample period July of 1926 to December of 1999, V_{FF} is on average 80 percent of V. This provides evidence that idiosyncratic risk is indeed the major component of total risk. Even more importantly, the idiosyncratic risk measures explain most of the time variation in average risk. A contemporaneous regression of V on V^{FF} yields an $\bar{R}^2$ of 70 percent. Table AII shows that V^{FF} is even stronger than V in predicting the next period's value-weighted returns. The t-statistic on V^{FF} is 2.41 compared to 2.06 on V (Table II). The coefficient on the market variance remains negative as before. When we include both measures of risk, the results are unchanged. The results for the full sample of 1928 to 1999 are similar—the average idiosyncratic risk measure is significant only at the 10 percent level when used together with business cycle variables.

Other Portfolios

We also explore the forecasting power of average stock variance to predict returns on portfolios other than the market. We use portfolios based on a double sort on book-to-market and size, and sorted by industry classification.[22] The results are presented in Table AIII. To conserve space, we present results only for the following regression estimated with the full sample period of 1926 to 1999

[21] We have also carried out this exercise for the market model. The results are virtually the same.

[22] The return data for these portfolios were obtained from Ken French's web site http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. We have also carried out this exercise for equal-weighted portfolio and the results are similar to those in Table V.

Table AII

Forecasts of Value-Weighted Portfolio Returns Based on Fama–French Factor Residuals

This table presents the results of a one-month-ahead predictive regression of excess value-weighted portfolio returns on lagged explanatory variables. The variable V_{vw} is the value-weighted volatility, calculated using CRSP daily data for the sample period July 1962 to December 1999 and using Schwert's daily data for the earlier sample period. The variable V^{FF} is the cross-sectional average of squared residuals. The residuals for each stock are calculated by a monthly time-series regression of the excess stock returns on the three Fama–French factors. The variable r_{vw} is the value-weighted portfolio return in excess of the three-month T-bill rate. *DP* is the logged dividend price ratio calculated as the difference between the log of last 12 month dividends and the log of the current price index of the CRSP value-weighted index. *RTB* is the relative three-month Treasury-bill rate calculated as the difference between T-bill and its 12-month moving average. *Term Spread* is the difference between the yield on long-term government bonds and T-bill. *Default Spread* is the difference between the yield on BAA- and AAA-rated corporate bonds. The sample period is August 1963 to December 1999 (437 monthly observations) in Panel A and February 1928 to December 1999 (863 monthly observations) in Panel B. The first row in each regression is the coefficient, the second row is the Newey–West adjusted t-statistic, and the third row is the bootstrapped p-value. The bootstrap experiment uses 10,000 replications and is carried out under the null of no predictability of returns.

	CNST	V_{vw}	V^{FF}	r_{vw}	*DP*	*RTB*	*Term Spread*	*Default Spread*	$\bar{R}^2$
				Panel A: Sample August 1963 to December 1999					
1.	0.007	−0.597							0.02%
	(3.21)	(−1.07)							
		[0.426]							
2.	−0.001		0.318						0.83%
	(−0.28)		(2.41)						
			[0.024]						
3.	0.000	−0.633	0.323						0.88%
	(0.02)	(−1.22)	(2.40)						
		[0.368]	[0.025]						
4.	0.012			−0.008	−0.000	−7.142	−0.322	1.586	4.00%
	(0.35)			(−0.13)	(−0.03)	(−3.05)	(−2.35)	(2.26)	
				[0.895]	[0.974]	[0.006]	[0.027]	[0.033]	
5.	0.012	−0.958		−0.035	−0.001	−7.545	−0.327	1.714	4.34%
	(0.33)	(−1.96)		(−0.70)	(−0.09)	(−2.94)	(−2.36)	(2.40)	
		[0.170]		[0.487]	[0.935]	[0.005]	[0.021]	[0.022]	
6.	0.033		0.287	−0.028	0.006	−6.320	−0.401	1.579	4.39%
	(0.89)		(1.83)	(−0.49)	(0.63)	(−2.64)	(−2.75)	(2.26)	
			[0.097]	[0.631]	[0.551]	[0.017]	[0.012]	[0.036]	
7.	0.035	−1.053	0.313	−0.059	0.006	−6.688	−0.414	1.719	4.84%
	(0.91)	(−2.30)	(1.85)	(−1.24)	(0.62)	(−2.59)	(−2.78)	(2.42)	
		[0.109]	[0.095]	[0.222]	[0.566]	[0.017]	[0.011]	[0.026]	
				Panel B: Sample February 1928 to December 1999					
1.	0.005	0.614							0.39%
	(1.91)	(0.69)							
		[0.513]							
2.	0.001		0.362						1.29%
	(0.20)		(1.84)						
			[0.077]						

Table AII—*Continued*

	CNST	V_{vw}	V^{FF}	r_{vw}	*DP*	*RTB*	*Term Spread*	*Default Spread*	$\bar{R}^2$
3.	0.000	0.285	0.326						1.27%
	(0.11)	(0.36)	(2.06)						
		[0.734]	[0.048]						
4.	0.014			0.103	0.003	− 5.270	− 0.053	0.314	1.66%
	(0.84)			(1.58)	(0.57)	(− 1.87)	(− 0.80)	(0.52)	
				[0.121]	[0.583]	[0.070]	[0.449]	[0.629]	
5.	0.016	0.635		0.114	0.003	− 5.318	− 0.029	0.015	1.92%
	(1.04)	(0.68)		(1.67)	(0.74)	(− 1.97)	(− 0.41)	(0.03)	
		[0.526]		[0.107]	[0.484]	[0.059]	[0.694]	[0.979]	
6.	0.031		0.322	0.068	0.008	− 5.051	− 0.083	− 0.099	2.20%
	(1.79)		(1.84)	(1.16)	(1.49)	(− 1.79)	(− 1.20)	(− 0.17)	
			[0.086]	[0.262]	[0.157]	[0.087]	[0.257]	[0.874]	
7.	0.030	0.391	0.271	0.081	0.007	− 5.115	− 0.063	− 0.217	2.21%
	(1.69)	(0.43)	(2.00)	(1.27)	(1.41)	(− 1.88)	(− 0.91)	(− 0.36)	
		[0.694]	[0.067]	[0.221]	[0.183]	[0.069]	[0.392]	[0.738]	

Table AIII

Forecasts of Portfolios Sorted on Characteristics

This table presents the results of the regression

$$r_{t+1} = \alpha + b\, V_{vwt} + c\, V_t^{lf} + \varepsilon_{t+1}$$

where r is the return (in excess of the three-month T-bill rate) on various portfolios based on characteristics. The variable V_{vw} is the value-weighted volatility, calculated using CRSP daily data for the sample period July 1962 to December 1999 and using Schwert's daily data for the earlier sample period. The variable V^{lf} is the average stock variance calculated using cross-sectional data. The table reports results for 25 size and book-to-market portfolios in Panel A and 17 industry portfolios in Panel B. Sample period is February 1928 to December 1999 (863 monthly observations). The p-values are obtained from a bootstrapped distribution with 10,000 replications.

Panel A: 25 Size and Book-to-Market Portfolios

	Size					Size				
B/M	Small	2	3	4	Large	Small	2	3	4	Large
			b					$p(b)$		
Low	0.844	− 0.429	0.427	0.412	0.094	0.603	0.584	0.716	0.631	0.902
2	− 0.390	0.365	0.476	0.677	0.113	0.841	0.767	0.663	0.593	0.882
3	0.455	0.607	0.751	0.414	0.222	0.765	0.632	0.514	0.703	0.828
4	0.423	0.670	0.367	0.879	0.840	0.762	0.594	0.753	0.449	0.501
High	0.309	0.471	0.854	1.393	0.473	0.811	0.728	0.523	0.382	0.804
			c					$p(c)$		
Low	0.683	0.447	0.427	0.228	0.209	0.172	0.051	0.039	0.013	0.015
2	0.869	0.422	0.290	0.297	0.176	0.016	0.050	0.016	0.010	0.036
3	0.651	0.485	0.343	0.328	0.213	0.014	0.036	0.011	0.006	0.035
4	0.736	0.481	0.363	0.323	0.280	0.027	0.026	0.033	0.030	0.046
High	0.636	0.417	0.511	0.402	0.406	0.049	0.057	0.009	0.044	0.071

Table AIII—*Continued*

B/M	Size: Small	2	3	4	Large	Size: Small	2	3	4	Large
	$\bar{R}^2$									
Low	2.44%	1.72%	2.43%	1.15%	0.86%					
2	3.99%	2.17%	1.64%	2.33%	0.64%					
3	3.56%	3.57%	2.67%	2.18%	0.94%					
4	5.21%	3.49%	2.17%	2.47%	2.03%					
High	3.02%	1.79%	3.28%	2.77%	0.49%					

Panel B: 17 Industry Portfolios

Industry	b	$p(b)$	c	$p(c)$	$\bar{R}^2$
Food	0.356	0.641	0.145	0.084	0.83%
Mining & Minerals	0.185	0.734	0.118	0.313	0.15%
Oil & Petroleum	0.659	0.508	0.056	0.581	0.40%
Textiles, Apparel, & Footwear	0.178	0.866	0.386	0.010	2.10%
Consumer Durables	−0.504	0.637	0.282	0.003	1.09%
Chemicals	0.763	0.492	0.219	0.039	1.66%
Drugs, Soap, Perfumes, & Tobacco	0.451	0.563	0.080	0.252	0.43%
Construction	0.524	0.610	0.384	0.001	2.64%
Steel	1.071	0.486	0.193	0.208	1.18%
Fabricated Products	0.648	0.475	0.110	0.331	0.66%
Machinery & Business Equipment	0.348	0.735	0.207	0.049	0.67%
Automobiles	0.816	0.576	0.381	0.006	2.48%
Transportation	0.328	0.722	0.330	0.021	1.56%
Utilities	0.229	0.713	0.207	0.053	0.90%
Retail Stores	−0.051	0.946	0.300	0.000	1.45%
Financial	0.266	0.760	0.336	0.006	1.72%
Other	−0.291	0.620	0.276	0.002	1.58%

(and the low-frequency volatility measure):

$$r_{pt+1} = a + b\, V_{vwt} + c\, V_t^{lf} + \varepsilon_{t+1}, \tag{A4}$$

where r_p is the excess return on the various characteristic-sorted portfolios. We also suppress the t-statistics for these regressions for space considerations. Panel A presents the results for 25 size and book-to-market sorted portfolios. For all the 25 portfolios, the coefficient on market volatility is insignificant. Twenty-one out of 25 size/book-to-market portfolios have significantly positive coefficients on the average stock variance. The average t-statistic on the coefficient "c" across all portfolios is 2.34 and the average $\bar{R}^2$ is 2.36 percent, which compare favorably with the earlier regressions. It is also noteworthy that the coefficient "c" declines with size across all book-to-market groups, implying that smaller stocks display higher predictability than larger stocks. There is no discernible trend in the p-values, however. In Panel B, we analyze 17 industry portfolios and find that in 10 of these the coefficient on average stock variance is significantly positive. The coefficient on market volatility remains insignificant in all cases.

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