Average Idiosyncratic Variance and Expected Stock Market Returns: Some Further Evidence

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Abstract

Using newly available CRSP data, we find that, consistent with the post-1963 evidence, the average idiosyncratic variance (IV) and stock market variance jointly forecast excess market returns over the 1927:Q1 to 1962:Q2 period. The forecasting relation, which is also very stable in the full sample, might reflect a close link between IV and investment opportunities, as suggested by the following three facts. First, high lagged returns on a portfolio of high IV stocks predict low future returns on the market as a whole. Second, returns on a hedging portfolio that is long in low IV stocks and short in high IV stocks perform just as well as HML in explaining the cross-section of stock returns. Third, variance of the hedging portfolio or of HML is closely correlated with the average IV, and the three variables have very similar predictive power for stock returns.

1.   Introduction

There is mixed empirical evidence on the relation between average idiosyncratic variance (IV) and future stock market returns. It has been found to be positive (Goyal and Santa-Clara (2003)), negative (Guo and Savickas (2006)), or statistically insignificant (Bali, Cakici, Yan, and Zhang (2005) and Wei and Zhang (2005)). This paper revisits the issue along two dimensions. First, we provide new empirical evidence by using (1) the newly available CRSP (the Center for Research in Security Prices) daily return data over the period January 1926 to June 1962 and (2) the OptionMetrics options-implied variance data over the period January 1996 to December 2005. Second, we formally investigate whether the average IV forecasts market returns because of its close relation with investment opportunities.

Over the period 1927:Q1 to 1963:Q4, the value-weighted CAPM-based IV is negatively related to future market returns when in conjunction with realized market variance (MV), and the relation between MV and future market returns is significantly positive. The results, which are consistent with those by Guo and Savickas (2006) for the period 1964:Q1 to 2002:Q4, hold up strongly over the full sample period 1927:Q1 to 2005:Q4 as well. We use quarterly data instead of monthly data (as in many other studies) because Ghysels, Santa-Clara, and Valkanov (2005) argue that realized variance is a function of long distributed lags of daily returns. As a robustness check, we also use monthly options-implied variances—which are arguably better measures of conditional variances than are realized variances—and find qualitatively similar results.

Our empirical evidence poses a challenge to the conjecture of a positive relation between the average IV and expected market returns, as advanced by Merton (1987), Malkiel and Xu (2001), and others. It is, however, consistent with Merton's (1973) ICAPM, in which the conditional equity premium is approximately a linear function of conditional market variance

and conditional variance of shocks to investment opportunities.[1] In particular, we argue that the average IV is a proxy of investment opportunities for at least three reasons. First, Cao, Simin, and Zhao (2006) suggest that firms with high IV are usually the firms with abundant growth options because managers of a levered firm are motivated to select the investment projects from their menu of growth options that increase the firm's idiosyncratic risk. These authors find that the average IV indeed correlates closely with standard measures of aggregate investment opportunities. Also, Berk, Green, and Naik (1999) show that discount rates—an important measure of investment opportunities—have significant effects on the valuation of growth options. Second, Pastor and Veronesi (2003) and others show that high IV stocks tend to be young and small; have low book-to-market ratio, low returns on equity, and high volatility of profitability; and pay no dividends. Thus, high IV stocks are likely to have long durations and are sensitive to discount-rate shocks.[2] Lastly, Lehmann (1990) suggests that the CAPM-based IV is a proxy for variance of the omitted risk factor(s)—e.g., discount-rate shocks in Campbell's (1993) ICAPM.[3] In this paper, we investigate several implications for the relation between the average IV and investment opportunities; however, we do not attempt to formally distinguish these mutually non-exclusive hypotheses.

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[1] This relation holds exactly if the loading of shocks to investment opportunities on market returns is constant.

[2] See Lettau and Wachter (2006), for example, for a formal treatment on the positive relation between durations and sensitivity to discount rate shocks. These authors also show that stocks with high durations have higher return volatility than stocks with low durations.

[3] Campbell's (1993) ICAPM provides a *mechanical* link between the time-series and cross-sectional predictability without explaining where stock return predictability comes from. Therefore, the economic underpinning of time-varying investment opportunities is an empirical issue. For example, Fama and French (1996) suggest that the value premium is a hedging risk factor because it reflects the distress risk. ICAPM suggests that one can test Fama and French's conjecture by showing that, as we find in this paper, the value premium explains the time-series stock return predictability as well. In the early empirical studies of ICAPM, e.g., Brennan, Wang, and Xia (2004), Campbell and Vuolteenaho (2004), Petkova (2006), and Hahn and Lee (2006), a subset of the commonly used stock return predictors serves as the state variables that describe investment opportunities. However, the forecasting power of these variables has been challenged (e.g., Goyal and Welch (2006)), so have the empirical ICAPM specifications (e.g., Chen and Zhao (2006)). Our approach is different from those used in the early studies. We first construct a hedging risk factor from the cross-section of stock returns following the ICAPM intuition, and then show that it performs quite well in explaining both the time-series and cross-sectional stock return predictability.

First, the value premium is one of the most successful empirical hedging risk factors, and has been commonly used in the empirical asset pricing literature. Fama and French (1996) suggest that it is a proxy for shocks to investment opportunities, and empirical studies by Brennan, Wang, and Xia (2004), Campbell and Vuolteenaho (2004), Petkova (2006), and Hahn and Lee (2006) find that it is closely related to discount-rate shocks. Consistent with the ICAPM interpretation, realized variances of market returns and the value premium jointly forecast excess market returns over the period 1963:Q4 to 2005:Q4. Interestingly, the average IV and realized value premium variance are very closely correlated with each other, with a correlation coefficient of about 88%. More importantly, the two variables have very similar forecasting power for market returns. The evidence suggests that the average IV might be a measure of variance of the hedging risk factor omitted from CAPM.

Second, if stocks with high IV are very sensitive to discount-rate shocks, high lagged returns on a portfolio of high IV stocks should predict low future returns on the market as a whole. This is because a positive shock to the discount rate leads stock prices to fall initially and to rise subsequently. To investigate this hypothesis, we follow Eleswarapu and Reinganum (2004) and use the returns on the portfolio of high IV stocks in the previous twelve quarters to forecast excess stock market returns in the following four quarters. As conjectured, the relation is found to be negative and statistically significant. By contrast, the predictive power is negligible for lagged returns on a portfolio of low IV stocks.

Third, Ang, Hodrick, Xing, and Zhang (2006, 2008) find that high IV stocks tend to have higher expected returns than do low IV stocks and the return difference cannot be easily diversified away. We construct a hedging portfolio that is long in high IV stocks and short in low IV stocks. We hypothesize that the portfolio return—dubbed as IVF—is a proxy for discount-rate shocks. As conjectured, we find that lagged IVF is positively correlated with future stock

market returns. Also, MV and realized variance of IVF jointly have significant predictive power for excess market returns over the period 1927:Q1 to 2005:Q4. Moreover, realized variance of IVF is closely correlated with the average IV and realized value premium variance, and these three variables have qualitatively similar forecasting power for market returns.

Lastly, data mining is always a concern in the empirical investigation of stock return predictability (e.g., Ferson et al. (2003)). To address this issue, we show that IVF performs just as well as or somewhat better than the value premium in explaining the cross-section of stock returns. By establishing a link between time-series and cross-sectional stock return predictability, as stressed by Fama (1991), this evidence suggests that data mining is unlikely the main driver of our empirical findings.

Our results shed light on the debate about stock return predictability across time. Early authors—e.g., Keim and Stambaugh (1986), Campbell (1987), Campbell and Shiller (1988), Fama and French (1989), Kothari and Shanken (1997), Pontiff and Schall (1998), Lamont (1998), Baker and Wurgler (2000), and Lettau and Ludvigson (2001)—find that some financial variables have significant forecasting power for excess stock market returns. Campbell and Cochrane (1999) and others have also developed rational expectations models to explain the observed stock return predictability. Goyal and Welch (2006), however, have conducted a comprehensive investigation of the existing evidence using the data updated to 2005, and found little support for out-of-sample predictability in long sample.[4] In this paper, we find that the average IV and MV jointly forecast stock market returns in-sample and out-of-sample over the period 1927:Q1 to 2005:Q4. Our theoretically motivated predictive variables have superior

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[4] Cochrane (2006) provides simulation results to show that for the size of samples commonly used in the empirical studies, the out-of-sample test based on the linear specification has low power to detect stock return predictability. Some recent studies, e.g., Lewellen (2004), Campbell and Thompson (2005), and Lettau and Nieuwerburgh (2006), have documented some out-of-sample predictability by using alternative forecasting specifications.

forecasting performance because they provide additional information about future stock returns beyond the variables considered in the earlier studies.

The remainder of the paper is organized as follows. We discuss the data in Section 2 and investigate the relation between the average IV and realized value premium variance in Section 3. We provide new empirical evidence on the relation between the average IV and excess stock market returns in Section 4 and test the hypothesis that IV is a proxy of investment opportunities in Section 5. We offer some concluding remarks in Section 6.

2. Data

We use the CRSP value-weighted stock market return as a proxy for aggregate market returns. The monthly risk-free rate is also obtained from CRSP; we construct the daily risk-free rate by assuming that it is constant within a month and that the daily risk-free rate compounds to the monthly risk-free rate. The excess stock market return is the difference between market returns and the risk-free rate.

Following Merton (1980), Andersen, Bollerslev, Diebold, and Labys (2003), and others, realized market variance is the sum of squared daily excess stock market returns in a quarter:

$$(1) \qquad MV_t = \sum_{d=1}^{D_t} (ER_{M,d})^2 ,$$

where $ER_{M,d}$ is the excess stock market return for day d and D_t is the number of trading days in quarter t. Following French, Schwert, and Stambaugh (1987), we also correct for the serial correlation in daily returns and find qualitatively similar results, which, for brevity, are not reported here.

Similar to Campbell, Lettau, Malkiel, and Xu (2001), Goyal and Santa-Clara (2003), and Guo and Savickas (2006), the value-weighted average idiosyncratic variance is

$$(2) \quad IV_t = \sum_{i=1}^{N_t} w_{i,t} \left[\sum_{d=1}^{D_{i,t}} e_{i,d}^2 + 2\sum_{d=1}^{D_{i,t}} e_{i,d} e_{i,d-1} \right] \quad \text{with} \quad w_{i,t} = \frac{v_{i,t-1}}{\sum_{j=1}^{N_t} v_{j,t-1}} ,$$

where N_t is the number of stocks in quarter t, $e_{i,d}$ is the idiosyncratic shock to stock i in day d,

$v_{i,t-1}$ is the market capitalization of stock i at the end of quarter t-1, and $w_{i,t}$ is the market share

of stock i. Throughout the paper, unless otherwise indicated, we include only common stocks in

the construction of the average IV. We calculate the daily idiosyncratic shock using CAPM:

$$(3) \quad e_{i,d} = ER_{i,d} - \hat{\alpha} - \hat{\beta} \cdot ER_{M,d} ,$$

where $ER_{i,d}$ is the excess return on stock i and $\hat{\alpha}$ and $\hat{\beta}$ are ordinary least squares (OLS)

estimates using daily data over the period d-130 to d-1. To obtain less-noisy estimates, we

require a minimum of 45 daily observations in the OLS regression. We also exclude stocks with

less than 15 return observations in a quarter and drop the autocorrelation term $2\sum_{d=1}^{D_{i,t}} e_{i,d} e_{i,d-1}$ from

equation (2) if $\sum_{d=1}^{D_{i,t}} e_{i,d}^2 + 2\sum_{d=1}^{D_{i,t}} e_{i,d} e_{i,d-1}$ is less than zero. For robustness, we construct three

measures of the average IV by using (1) 100 largest stocks, (2) 500 largest stocks, and (3) all

stocks.[5] We also construct the equal-weighted average IV assuming $w_{i,t} = \frac{1}{N}$ in equation (2).

Our quarterly sample for the average IV spans the 1926:Q4 to 2005:Q4 period.

Panel A, Figure 1 plots both equal-weighted (thick line) and value-weighted (thin line)

average IV constructed from the 100 largest stocks. The two measures are almost perfectly

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[5] UNITED GAS IMPT CO had a return of 317.592% on August 20, 1943. This single observation will cause a big spike in our measures of idiosyncratic variance for 1943:Q3 if it is included in our calculation. A daily return of over 300% mainly reflects the idiosyncratic shock; therefore, we exclude it because we interpret the average IV as a proxy for the variance of the risk-factor omitted from CAPM. For robustness, we also experiment with filtering out daily returns higher than 100% and find that such a filter has negligible effects on our measures of the average IV.

correlated with each other over the period 1926:Q4 to 2005:Q4. There are a few big spikes in the late 1920s and early 1930s, during which the stock market was extremely volatile due to the confounding effects of the 1929 stock market crash and the subsequent Great Depression. Panel B plots the average IV for the 500 largest stocks. There are some noticeable differences between the equal-weighted and the value-weighted measures in the early period; however, the two measures have moved closely to each other since the late 1940s. Lastly, panel C plots the average IV for all stocks. We find substantial difference between the two measures. Consistent with Campbell, Lettau, Malkiel, and Xu (2001), the equal-weighted average IV has trended upward since the late 1940s, although it decreased substantially at the end of our sample. The trend, however, is much less pronounced for the value-weighted average IV, which is also substantially lower than its equal-weighted counterpart.

To summarize, the difference between the equal- and value-weighted average IVs is much larger for small stocks than big stocks. One possible explanation is that the average IV has two components—variance of the risk-factor omitted from CAPM and variance of "true" idiosyncratic shocks. Because small stocks are more vulnerable to idiosyncratic shocks than big stocks, we are likely to find that equal-weighted average IV is higher than its value-weighted counterpart, especially for smaller stocks. This conjecture also implies that, as we confirm below, the value-weighted average IV is a better proxy for the conditional variance of the risk factor omitted from CAPM than its equal-weighted counterpart.

Figure 2 plots realized stock market variance (thick line, left scale) along with excess stock market returns (thin line, right scale). Similar to the average IV, we observe a few big spikes in realized stock market variance, for example, during the 1929 stock market crash, the subsequent Great Depression, and the 1987 stock market crash. To investigate whether the spikes

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have significant effects on our statistical inference, we also use a log transformation for stock market variance and the average IV in the empirical analysis.

Table 1 provides summary statistics for the three main variables used in the paper: Excess stock market return (RET), realized stock market variance (MV), and the value-weighted average IV constructed from the 100 largest stocks. Consistent with early studies, the contemporaneous relation between stock market returns and variance is negative over the period 1926:Q4 to 2005:Q4. Interestingly, the contemporaneous relation between market returns and the average IV is positive. The latter result is consistent with Duffee (1995), who finds a positive relation between the firm-level stock return and volatility. We also observe relatively strong comovement between stock market variance and the average IV, with a correlation coefficient of about 0.64.

Lastly, panel B, Table 1 shows that both stock market variance and idiosyncratic variance are serially correlated, with an autocorrelation coefficient of 0.50 and 0.62, respectively. These results suggest that lagged realized variances might help forecast stock market returns because they provide a good indication of future variances.[6] Thus, we primarily use lagged stock market variance and lagged average IV as proxies for conditional stock market variance and conditional variance of the risk factor omitted from CAPM, respectively.

Note that both average IV and MV are substantially less persistent than the predictive variables commonly used in the early studies; therefore, as we show below, they are potentially less vulnerable to the small sample bias emphasized by Stambaugh (1999). Several studies, e.g., Christensen and Prabhala (1998) and Fleming (1998), find that implied variance estimated from

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[6] Guo, Savickas, Wang, and Yang (2007) find qualitatively similar results in the estimation of ICAPM by using both the realized variance model and the GARCH model. They also provide simulation results to show that both models provide reliable inference in samples with size similar to that of the post-World War II period. In particular, in the simulation, these authors use the value premium as a proxy for the hedging factor and estimate ICAPM with a bivariate GARCH model and daily data. Then they use simulated daily data from the GARCH estimation to estimate ICAPM with both quarterly realized variance model and monthly bivariate GARCH model, and find that both models are able to capture the relation between the first and second moments of the risk factors.

options contracts provides a better measure of conditional stock variance than lagged realized variance. Consistent with their finding, we show that using implied variance substantially enhances stock return predictability. Because the data of implied variance are available for a short period, we mainly rely on realized variances in our empirical analysis, however.

3. Average Idiosyncratic Variance and Variance of the Value Premium

Some recent studies, e.g., Campbell and Vuolteenaho (2004), Brennan, Wang, and Xia (2004), Petkova (2006), and Hahn and Lee (2006), find that over the post-1963 sample, the value premium is closely related to discount-rate shocks. To further test this conjecture, we construct realized value premium variance using daily data obtained from Ken French at Dartmouth College for the period 1963:Q3 to 2005:Q4. If the value premium is a proxy for discount-rate shocks, we expect a *negative* relation between realized value premium variance and future market returns, while the relation should be positive for realized stock market variance.[7]

Table 2 presents the OLS (ordinary least squares) regression results. We find that realized value premium variance (V_HML) is negatively related to one-quarter-ahead excess stock returns; the relation is statistically insignificant, however. Interestingly, when combined with realized market variance (MV), the coefficient of realized value premium variance remains negative and becomes significant at the 1% level. Moreover, as expected, the relation between realized market variance and future market returns is significantly positive. Therefore, consistent with ICAPM, stock market returns are predictable by conditional variances of risk factors.

We have argued that the CAPM-based average IV is a proxy for investment opportunities, e.g., variance of the hedging factor omitted from CAPM. Consistent with this

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[7] See Campbell (1993) and Campbell and Vuolteenaho (2004) for the derivation of the negative relation between the expected market return and conditional variance of discount-rate shocks. If the value premium reflects risks other than discount-rate shocks, we still expect a negative relation between the expected market return and conditional variance of the value premium because market returns are negatively correlated with the value premium.

hypothesis, Figure 3 shows that over the period 1963:Q3 to 2005:Q4, the value-weighted average IV constructed from the 100 largest stocks (thin line) moves closely with realized value premium variance (thick line), with a correlation coefficient of about 88%. Moreover, Row 3, Table 2 shows that, when we add the average IV to the forecasting equation, the predictive power of realized value premium variance becomes statistically insignificant, so does the average IV. This result suggests that, as hypothesized, the average IV and realized value premium variance contain similar information about future stock prices.

Using the value premium as a risk factor, however, has an important limitation because recent studies, e.g., Campbell and Vuolteenaho (2004), Ang and Chen (2005), Petkova and Zhang (2005), and Fama and French (2005), show that it is a poor proxy of systematic risk in the pre-1963 sample. By contrast, we show below that the relation between the average IV and stock market returns is quite stable over the 1926 to 2005 period.

4.   Average Idiosyncratic Variance and Expected Market returns: 1927:Q1 to 2005:Q4

A.   Forecasting One-Quarter-Ahead Excess Market Returns

Table 3 presents the OLS regression results of forecasting one-quarter-ahead excess stock market returns. We use the value-weighted average IV constructed from the 100 largest stocks; as we show later, we find essentially the same results using the value-weighted average IV constructed from the 500 largest stocks or all stocks. We calculate the t-value using the Newey-West (1987) corrected standard error with four lags.

Panel A, Table 3 reports the results for the full sample spanning the period 1927:Q1 to 2005:Q4. The predictive power of realized market variance by itself is statistically insignificant (row 1); and the average IV alone does not forecast market returns either (row 2). When we include both variables in the forecasting regression, however, the effect becomes statistically

significant at the 5% and 1% levels for realized market variance and the average IV, respectively—with an adjusted R-Squared of about 4% (row 3). Also, the Wald test indicates that their joint forecasting power is statistically significant at any conventional level.

In row 3 of Table 3, the coefficient of realized stock market variance is positive, with a point estimate of 2.28. Therefore, consistent with ICAPM, there is a positive relation between conditional stock market returns and variance. The coefficient of the average IV is negative, with a point estimate of –1.98. Therefore, the result that realized market variance and the average IV forecast stock market returns jointly but not individually reflects an omitted variable problem because the average IV and market variance are positively correlated (Table 1).[8]

The negative relation between the average IV and expected market returns is consistent with the hypothesis that the average IV is a proxy for the conditional variance of a hedging risk factor: For example, realized value premium variance is negatively related to expected returns in Table 2. Alternatively, there might be a direct link between discount rates and the average IV. When the expected discount rate falls, the number of risky projects that a firm's managers can choose from should increase, so should the firm's idiosyncratic risk.

For robustness, Table 3 also reports the results of two subsamples: 1927:Q1 to 1963:Q4 (panel B) and 1964:Q1 to 2005:Q4 (panel C). The results from the first subsample, which has never been investigated before, are very similar to those obtained from the full sample. When they enter the forecasting regression separately, neither realized market variance (row 4) nor the average IV (row 5) is a significantly predictor of market returns. However, the effect of these variables becomes significant at the 5% and 1% levels for market variance and the average IV, respectively, when both variables are included in the forecasting equation (row 6). Also, in the

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[8] Because of the correlation between realized market variance and the average IV, there is a potential concern with multicollinearity. However, multicollinearity cannot explain our results because it usually leads to low t-statistics, in contrast with the increase of t-statistics when both variables are included. Moreover, the characteristic-root-ratio test proposed by Belsley, Kuh, and Welsch (1980) confirms that multicollinearity is unlikely to plague our results.

multivariate regression, while the coefficient of realized market variance is positive, it is negative for the average IV. Consistent with Guo and Savickas (2006), we find similar results for the second subsample as well. Note that the coefficients of both variables are quite stable in two subsamples. This result explains that, as we show below, realized market variance and the average IV have significant out-of-sample predictive power for stock returns.

B.   *Some Robustness Checks*

Figures 1 and 2 show that the average IV and realized market variance have a few big spikes. To investigate whether the results reported in Table 3 are sensitive to the influence of these potential outliers, we use log transformations of both average IV and market variance in the forecasting regression and find qualitatively similar results.

Table 1 shows that both realized market variance and the average IV are serially correlated; and they are also correlated with stock market returns. Therefore, the OLS estimates can be potentially biased in small samples (see, e.g., Stambaugh, 1999). To address this issue, we use the bootstrapping approach to obtain the empirical distribution of the t-statistic. In particular, we assume that excess market returns, realized stock market variance, and the average IV follow a joint VAR(1) process with the restrictions under the null hypothesis that the expected excess market return is constant. We estimate the VAR system using the actual data and then generate the simulated data 10,000 times by drawing estimated error terms with replacements. We find that the empirical distribution of the t-statistic is very similar to the asymptotic distribution. The small sample bias has small effects on our inference possibly because Table 1 shows that our forecasting variables are substantially less persistent than are those predictive variables cautioned by Stambaugh (1999), for example, the dividend yield. For brevity, in the remainder of the paper, we make inference using the asymptotic distribution of the t-statistic.

Because small stocks are more vulnerable to "true" idiosyncratic shocks, using big stocks or the value weighting scheme to construct the average IV may provide a better measure for the conditional variance of the omitted risk factor. To illustrate this point, we investigate some alternative measures of the average IV. We find qualitatively similar results using the value-weighted measures constructed from the 500 largest stocks and all stocks. The results are mixed for the equal-weighted measures, however. We find similar results for the equal-weighted measure constructed from the 100 largest stocks, while the results are substantially weaker for the equal-weighted average IV constructed from the 500 largest stocks and all stocks. For robustness, we also repeat the above analysis using log transformations of both realized market variance and the average IV, and find similar results. To summarize, the average IV constructed from large stocks performs better than the average IV constructed from small stocks in the forecast of market returns. For brevity, in the remainder of the paper, we use the value-weighted IV constructed from the 100 largest stocks.

C.   *Forecasting One-Year Ahead Excess Stock Market Returns*

Table 4 investigates whether realized market variance and the average IV at the last quarter of a year forecast the excess market return in the following year. Because we have substantially fewer observations for the annual regression, the results are potentially more vulnerable to outliers than are those obtained from the quarterly regression. To partially address this concern, we use log transformations of the forecasting variables in panel A. Consistent with the results obtained from quarterly data, log average IV is negatively and significantly related to the one-year-ahead excess stock market return. Also, log realized market variance is positively related to future stock returns; however, such a relation is statistically insignificant possibly

because of the relatively small sample size. Overall, the Wald test indicates that their joint predictive power is statistically significant at the 5% level.

Figures 1 and 2 show that both the average IV and realized stock market variance have a dramatic spike following the 1929 stock market crash. If we drop this potential outlier and run the regression using the sample period 1932 to 2005, panel B of Table 4 shows that the both log realized market variance and log average IV have significant effects on future stock market returns. Consistent with the results obtained from quarterly data, while the effect of market variance is positive, it is negative for the average IV. Also, the adjusted R-squared increases substantially from 3.2% in panel A to 7.9% in panel B, indicating that the 1929 crash does have a confounding effect on the inference. Similarly, in panel C, we use the raw predictive variables to forecast stock returns over the period 1932 to 2005 and find qualitatively similar results.

Consistent with the results in Bali, Cakici, Yan, and Zhang (2005) and Zhang and Wei (2005), we find that the average IV and market variance have negligible predictability for market returns in monthly data (not reported here). The result might reflect the fact that realized variances are poor measures of conditional variances at the monthly frequency. In subsection F, we show that the average IV and market variance have significant predictive power for the one-month-ahead excess stock return by using options-implied variances.

D.   *Control for Other Predictive Variables*

This subsection compares the forecasting power of realized market variance and the average IV with that of the variables commonly used in the existing literature. We consider a total of fourteen additional forecasting variables, which are obtained from Amit Goyal at Emory University. Table 5 shows that the coefficient of realized market variance remains statistically significant at the 5% level except when we control for the net equity expansion (NTIS), which is

the ratio of twelve-month moving sums of net issues by NYSE listed stocks divided by the total market capitalization of NYSE stocks. Similarly, the coefficient of the average IV is always statistically significant at the 5% level. Overall, the Wald test indicates that two forecasting variables are jointly significant at the 5% level except when we control for the consumption-wealth ratio (CAY) proposed by Lettau and Ludvigson (2001).[9]

To summarize, realized stock market variance and the average IV jointly provide information about future stock returns beyond the variables commonly used in the early studies.

E.   *Out-of-Sample Forecasts*

As in Lettau and Ludvigson (2001), we compare the performance of our forecasting model with a benchmark model of constant stock market returns. We use three test statistics to gauge the relative performance of the two models: The mean-squared error (MSE) ratio; the encompassing test (ENC-NEW) proposed by Clark and McCracken (2001); and the equal forecast accuracy test (MSE-F) proposed by McCracken (1999). As in Lettau and Ludvigson (2001), we use the first one-third of the sample (1927:Q1 to 1953:Q1) for the initial in-sample regression and then make out-of-sample forecast for the remainder of the sample recursively. For ENC-NEW and MSE-F tests, we report both asymptotic and bootstrap 5% critical values.

The first row of Table 6 reports the results for realized stock market variance and the average IV in levels. The MSE ratio between the forecasting model and the benchmark model is 0.95, suggesting that the forecasting model has substantially smaller squared forecasting errors than does the benchmark model. Similarly, the ENC-NEW test statistic is 12.66, which is

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[9] CAY is the error term from the cointegration relation among consumption, wealth, and labor income. Goyal and Welch (2006) find that CAY does have out-of-sample predictive power for stock returns but caution that it might come from a look-ahead bias because CAY is estimated using the full sample. Guo and Savickas (2006), however, argue that the average IV and CAY have similar predictive power for stock returns because they both are proxies of investment opportunities.

substantially above the 5% asymptotic and bootstrap critical values. Therefore, the difference between the forecasting model and the benchmark model is statistically significant. We obtain the same conclusion using the MSE-F test. The second row of Table 6 shows that the results are qualitatively similar by using log realized market variance and log average IV.

Figure 4 plots the recursive MSE ratio of the forecasting model (in row 1 of Table 6) to the benchmark model of constant stock returns through time. The horizontal axis denotes the starting date for the out-of-sample forecast: For example, the value corresponding to June 1953 is the MSE ratio over the forecast period 1953:Q2 to 2005:Q4. We choose the range 1953:Q2 to 2000:Q4 for the starting forecast date; therefore, we use at least 20 observations for the calculation of the MSE ratio. The MSE ratio is always less than 1, indicating that realized market variance and the average IV jointly have reliable out-of-sample forecasting power for excess stock market returns. Similarly, Figure 5 plots the difference in MSE between the benchmark model of constant stock returns and the forecasting model (in row 1 of Table 6). It shows that our results are not influenced by any particular episode.

To summarize, realized stock market variance and the average IV have significant out-of-sample forecasting power for excess stock market returns.

F.   *Alternative Measures of Stock Market Variance and Idiosyncratic Variance*

We calculate realized variance using 5-minute S&P500 cash index over the period 1986:Q1 to 2004:Q4—the longest sample available to us—and plot it (thick line) in Figure 6. For comparison, we also plot realized variance constructed using daily stock return data (thin line). In general, the two measures move closely to each other, with a correlation coefficient of 0.77. However, we do observe an important difference: Realized market variance is substantially lower for 5-minute data than daily data in 1987:Q4.

Table 7 presents the OLS regression results of forecasting stock market returns using realized stock market variance constructed from both daily (panel A) and 5-minute (panel B) data. The results for both measures are qualitatively similar; however, 5-minute data generate an adjusted R-squared substantially higher than do daily data. The difference likely reflects the fact that, as pointed out by Merton (1980) and Andersen, Bollerslev, Diebold, and Labys (2003), we can estimate realized variance more precisely by using higher-frequency data.

In panel C of Table 7, we also use the end-of-quarter implied variance estimated from options contracts on the S&P 100 index as a proxy for conditional stock market variance. To be comparable with the results obtained from the 5-minute data, we use the period 1986:Q2 to 2004:Q4. By contrast with realized variance constructed from both daily and 5-minute data, implied variance has a significantly positive effect on future stock market returns when it is the only forecasting variable (row 6). Jointly, the forecasting power of both implied variance and the average IV is significant at the 1% level, with an adjusted R-squared of over 15% (row 7).

Lastly, we construct the daily value-weighted idiosyncratic variance using stock-level options-implied variances obtained from the OptionMetrics database. We use the end-of-period observations for both monthly and quarterly data, while we find qualitatively similar result using the monthly and quarterly averages. To improve the efficiency of estimations, we also use the end-of-period implied variance as a proxy for conditional stock market variance.

Despite the relative short sample, which spans the period February 1996 to December 2005, Table 8 shows that the results are qualitatively similar to those obtained using quarterly realized variances. Panel A report the regression results for monthly data. While the average IV by itself has insignificant predictive power (row 2), its effect becomes significant at the 1% level after we also include market variance in the forecasting equation (row 3). Also note that the stock market variance has a substantially higher t-statistic in the multivariate regression (row 3)

than in the univariate regression (row 1). The Wald test indicates that the joint predictive power of the two variables is significant at the 1% level.

Panel B, Table 8 shows that evidence of stock return predictability is substantially stronger in quarterly data than in monthly data: Over the same sample period, the adjusted R-squared is about 23% for quarter data, compared with 4% for monthly data. This evidence is consistent with the fact that we find significant stock return predictability using realized variances in quarterly data but not in monthly data.

To summarize, using better measures of conditional stock market variance and idiosyncratic variance substantially enhances stock return predictability. Also, we are more likely to detect stock return predictability in quarterly data than in monthly data.

5.   Is the CAPM-Based Idiosyncratic Variance a Proxy for Risk? Further Tests

We have shown that the average IV has significant forecasting power for stock market returns when combined with market variance. One possible explanation of this result is that the average IV is a proxy for conditional variance of the hedging factor omitted form CAPM. This interpretation is plausible because the average IV is closely correlated with realized value premium variance—which is arguably a proxy of systematic risk—and the two variables have similar forecasting power for stock returns. In this section, we conduct further tests on whether the CAPM-based IV is a proxy for risk.

A.   Lagged Portfolio Returns and Expected Stock Market Returns

In the introduction, we argue that high IV stocks are more sensitive to discount-rate shocks than low IV stocks. Thus, we expect a negative relation between lagged returns on stocks with high IV and future excess stock market returns. To address this issue, we first sort stocks

equally into two portfolios by size, and then within each size portfolio we sort stocks equally into three portfolios by IV. The portfolio returns are calculated using the value weight.

Eleswarapu and Reinganum (2004) find that high lagged returns on growth stocks predict low future stock market returns, while the predictive power is negligible for value stocks. As we show in the next subsection, there is a very close relation between the value effect and the IV effect. Therefore, to be comparable with the results reported in Eleswarapu and Reinganum, we follow their approach closely here. In particular, over the post-1950 period, we use the returns on stocks with high IV in the previous 12 quarters to forecast excess stock market returns in the following 4 quarters. The choice of the post-1950 sample also reflects the fact that the volatile stock market in the pre-1950 sample, which includes the periods of the 1929 crash, the Great Depression, and the World War II, makes it difficult to draw any precise inference.

Panel A, Table 9 presents the regression results, with the p-value obtained through bootstrapping in parentheses. As hypothesized, for both small and big stocks, lagged returns on the stocks with high IV is negatively related to future stock market returns, and such a relation is significant at the 5% level. By contrast, the predictive power is statistically insignificant for lagged returns on stocks with low IV.

We also construct a hedging portfolio, IVF, in a way similar to that of Fama and French (1996) in their construction of the value premium. In particular, for both small and big stocks, we calculate the return difference between the portfolio with low IV stocks and the portfolio with high IV stocks. IVF is then the equal-weighted average of such a difference across small and big stocks. Panel B, Table 9 shows that lagged returns on the hedging portfolio also forecasts excess stock market returns. The lagged returns on the hedging portfolio are positively related with future stock market returns because the hedging portfolio has a short position in high IV stocks. By contrast, the predictive power of lagged stock market returns is insignificant at the 10% level.

B. *IVF and the Cross-Section of Stock Returns*

Consistent with the conjecture that IV is a proxy for loadings on the discount-rate shock, we have found that high lagged returns on stocks with high IV predict low future stock market returns. An immediate implication of this result is that IVF—the return on the hedging portfolio that is long (short) in stocks with low (high) IV—should help explanation the cross-section of stock returns. Ang, Hodrick, Xing, and Zhang (2006, 2008) show that the return difference between stocks with low IV and stocks with high IV cannot be easily diversified away. One possibility is that IVF could be a proxy for the discount-rate shock. In particular, because Eleswarapu and Reinganum (2004) find that high lagged returns on growth stocks also forecast low future stock market returns, IVF should have explanatory power similar to that of the value premium. This conjecture is plausible also because Brennan, Wang, and Xia (2004), Campbell and Vuolteenaho (2004), Petkova (2006), and Hahn and Lee (2006) show that the value premium is related to shocks to state variables that forecast stock market returns.

We find that IVF is indeed closely correlated with the value premium, with a correlation coefficient of about 45% over the sample period 1964:Q1 to 2005:Q4. More importantly, Table 10 shows that IVF performs as well as or somewhat better than the value premium in explaining the cross-section of returns on the 25 Fama and French (1996) portfolios sorted by size and the book-to-market ratio. In panel A, IVF is significantly priced in the Fama and MacBeth (1973) regression. Interestingly, the risk premium on the excess stock market return (MKT) is also significantly positive; however, the size premium (SMB) is not priced in our sample. Overall, the three risk factors jointly account for 83% variation in cross-sectional average portfolio returns, compared with 79% for the Fama and French (1996) three-factor model.

Panels B to D of Table 10 provide diagnostic tests using the stochastic discount factor (SDF) models, in which the SDF is a linear function of the proposed risk factors. For robustness,

we use three different weighing matrices: Identity weighting matrix (panel B); inverted covariance matrix of the portfolio returns, as advocated by Hansen and Jagannathan (1997); and Hansen's (1982) optimal weighting matrix. For the first two weighting matrices, we test the models using the distance measure (Dist) proposed by Jagannathan and Wang (1996) and Hansen and Jagannathan (1997). We use Hansen's (1982) J-test for the optimal weighting matrix. We find that the IVF performs substantially better than the value premium. In particular, while the Fama and French 3-factor model is overwhelmingly rejected in all three specifications, the model with IVF as a risk factor is not rejected at the 1% level for the identity weighting matrix; at the 5% level for the Hansen and Jagannathan weighting matrix; and at the 10% level for the optimal weighting matrix. Ahn and Gadarowski (2004) have noted that the test based on the distance measure tends to reject the true model too often in small samples. With this caveat in mind, IVF appears to perform quite well in explaining the cross-section of stock returns.

C.   *Realized Variance of IVF and Expected Excess Stock Market Returns*

We have shown that the hedging factor IVF performs as well as or somewhat better than the value premium. Table 11 investigates the time-series ICAPM implication that realized variance of IVF (V_IVF) should forecast excess stock market returns. Panel A shows that over the full sample spanning the period 1927:Q1 to 2005:Q4, realized variance of IVF by itself has negligible predictive power for stock market returns (row 1). However, its effects become significantly negative after we also include realized stock market variance in the forecasting equation (row 2). Again, realized stock market variance is positively related to future stock market returns, and such a relation is statistically significant at the 10% level. Overall, the Wald test indicates that the joint predictive power of realized variances of market returns and IVF is significant at the 5% level. We also find similar results in two subsamples (panels B and C).

We have shown that IVF is closely correlated with the value premium over the period 1964:Q1 to 2005:Q4. Thus, it is not a surprise that realized variance of IVF is closely correlated with realized value premium variance, with a correlation coefficient of about 88%. Moreover, the two variables also have very similar predictive power for stock returns. For brevity, these results are not reported here but are available on request.

Realized variance of IVF and the average IV are also closely correlated with each other, with a correlation coefficient of about 83% over the period 1926:Q4 to 2005:Q4. To investigate whether the forecasting power of the average IV mainly come from its close relation with the conditional variance of the discount-rate shock, we orthogonalize the average IV by realized variance of IVF and use the residual (IV^+) to forecast stock market returns. Table 11 shows that IV^+ is statistically insignificant at the conventional level in the two subsamples. Similarly, it is only marginally significant in the full sample, with an adjusted R-squared much smaller than those reported in Table 3. Therefore, as hypothesized, the forecasting power of the average IV mainly comes from its close relation with the conditional variance of the discount rate shock.

D.   *Forecasting Returns on Hedging Portfolios*

If IVF is a proxy for the return on the hedging portfolio, Campbell's (1993) ICAPM indicates that it is predictable by its own variance and the variance of the stock market return. In particular, we expect that IVF is positively correlated with its own variance and negatively correlated with stock market variance. This conjecture is strongly confirmed by the results presented in Table 12, which also shows that the results are qualitatively similar by using the average IV as a proxy for the variance of the hedging factor.

E. Some Discussions

We have shown that when in conjunction with market variance, the average CAPM-based IV forecasts stock market returns over the period 1927 to 2005. Also, IVF—the return on a hedging portfolio that is long in stocks with low IV and short in stocks with high IV—is a significantly priced risk factor. Moreover, the average IV and realized variance of IVF are closely correlated with each other and the two variables have similar predictive power for stock market returns. One possible explanation is that IV is a proxy for loadings on the discount-rate shock and the average IV moves closely with the variance of the discount-rate shock.

If IVF is a priced risk factor, we can use it to control for systematic risks in the construction of the idiosyncratic shock. Controlling for IVF, however, has negligible effects on our measure of the average IV. We find a similar result using the other commonly-used empirical risk factors, e.g., the value premium and the momentum profit. While we cannot completely rule out the possibility of data mining, we offer three other alternative explanations.

First, IVF is just an empirical risk factor and has measurement errors. For example, Table 10 shows that it has substantial pricing errors, although we cannot reject the model at some conventional significance levels. More importantly, at the individual stock level, idiosyncratic risk accounts for a large portion of variation in a stock's price and thus leads to the imprecise estimation of the factor loadings. Among all risk factors considered here, only the market return accounts for a significant portion of variation in individual stock returns. Together, these two concerns suggest that including IVF as an additional risk factor might not appropriately account for the systematic risk omitted from CAPM at the firm level.

Second, as mentioned in introduction, Cao, Simin, and Zhao (2006) argue that firms with high IV are usually the firms with abundant growth options. That is, variance of stock-level idiosyncratic shocks is not necessarily idiosyncratic; it can be correlated with changes in

investment opportunities. For example, Agarwal, Bharath, and Viswanathan (2004) conduct an event study using a sample of "brick and mortar" firms that announced their initiation of eCommerce in the late 1990s. They find that these firms experienced significant increases in both stock prices and volatility after the announcements. Similarly, Mazzucato (2002) studies the U.S. auto industry from 1899 to 1929 and the U.S. PC industry from 1974 to 2000, and Pastor and Veronesi (2005) examine American railroads from 1830 to 1861. These authors find that, in these industries, firm volatility—as measured with both real variables and stock prices—increases sharply when there are radical technological changes, which also initially drove up the stock prices of the firms in these industries. To illustrate this point, we construct the average industry IV using 20 industry portfolios, as defined in Grinblatt and Moskowitz (1999). Figure 7 shows that although the average industry IV is substantially smaller than the average firm IV, the two move closely to each other; and they have similar forecasting power for stock market returns. Interestingly, by contrast with the average firm IV, controlling for IVF has some noticeable effects on the measure of the average industry IV, although it does not qualitatively change our main result possibly because IVF is a noisy measure of the omitted risk factor.[10] The latter result suggests that both the first and the second explanations might be relevant.

Lastly, idiosyncratic variance might also be a measure of dispersion of opinion, which leads a stock to be overpriced initially but to suffer a capital loss eventually (Miller, 1977). To address this possibility, following Diether, Malloy, and Scherbina (2002), we use dispersion of analysts' earning forecasts obtained from the IBES database as a measure of dispersion of opinion and aggregate them across stocks using both equal- and value-weighting schemes. We find that the average dispersion of analysts' earning forecasts has negligible forecasting power for stock market returns either by itself or in conjunction with conditional stock market variance.

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[10] For brevity, these results are not reported here but are available on request.

Also, Miller's hypothesis cannot explain (1) why the predictive power of the average IV is closely related to that of realized variance of the value premium or IVF and (2) why IVF helps explain the cross-section of stock returns.

6. Conclusion

We propose a couple of forecasting variables following the intuition of Merton's (1973) ICAPM, in which conditional excess stock market returns are a linear function of conditional stock market variance and conditional variance of the hedging risk factor(s). While the hedging risk factor is not directly observable, we argue that the average CAPM-based idiosyncratic variance is a potentially good proxy for variance of the hedging factor. Over the period 1927:Q1 to 2005:Q4, the average idiosyncratic variance and realized stock market variance jointly forecast stock market returns in sample and out of sample, and this result holds up in a number of robustness checks.

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Table 1 Summary Statistics: 1926:Q4 to 2005:Q4

Note: The table reports summary statistics of the CAPM-based average idiosyncratic variance constructed using the 100 largest stocks, IV; realized stock market variance, MV; and the excess stock market return, RET.

	RET	MV	IV
Panel A. Cross-Correlation			
RET	1.000		
MV	-0.106	1.000	
IV	0.139	0.643	1.000
Panel B. Univariate Statistics			
Mean	0.021	0.008	0.013
Standard Deviation	0.114	0.014	0.014
Autocorrelation	-0.080	0.504	0.619

Table 2 Average Idiosyncratic Variance and Value Premium Variance: 1963:Q4 to 2005:Q4

Note: The table reports OLS regression results of forecasting the one-quarter-ahead excess stock market return. MV is realized stock market variance; IV is the CAPM-based average idiosyncratic variance constructed using the 100 largest stocks; and V_HML is realized value premium variance. We calculate the t-value using the Newey-West corrected standard error. ***, **, and * denote significant at the 1%, 5%, and 10% levels, respectively.

	MV	t-value	IV	t-value	V_HML	t-value	Adjusted R-Squared
1					-3.939	-1.118	0.002
2	2.598**	2.236			-9.255***	-2.981	0.036
3	2.888**	2.255	-1.534	-1.322	-2.011	-0.297	0.039

Table 3 Forecasting One-Quarter-Ahead Excess Stock Market Return Using Variances

Note: The table reports OLS regression results of forecasting the one-quarter-ahead excess stock market return. MV is realized stock market variance and IV is the CAPM-based average idiosyncratic variance constructed using the 100 largest stocks. Wald test is the test for the joint significance of MV and IV. We calculate the t-value using the Newey-West corrected standard error. ***, **, and * denote significant at the 1%, 5%, and 10% levels, respectively.

	MV	t-value	IV	t-value	Wald Test p-value	Adjusted R-Squared
			Panel A 1927:Q1 to 2005:Q4			
1	0.941	1.518				0.009
2			-0.587	-1.333		0.002
3	2.284**	2.343	-1.977***	-4.198	0.000	0.043
			Panel B 1927:Q1 to 1963:Q4			
4	0.762	1.041				0.003
5			-0.456	-0.896		-0.004
6	2.309**	2.009	-2.177***	-3.089	0.008	0.031
			Panel C 1964:Q1 to 2005:Q4			
7	1.470*	1.802				0.011
8			-0.738	-1.326		0.003
9	2.872**	2.274	-1.824***	-3.442	0.003	0.044

Table 4 Forecasting One-Year-Ahead Excess Stock Market Return

Note: The table reports OLS regression results of forecasting the one-year-ahead excess stock market return. MV is realized stock market variance and IV is the CAPM-based average idiosyncratic variance constructed using the 100 largest stocks. We use the non-overlapping data: MV and IV are quarterly variances at the last quarter of the previous year. Wald test is the test for the joint significance of MV and IV. We calculate the t-value using the Newey-West corrected standard error. ***, **, and * denote significant at the 1%, 5%, and 10% levels, respectively.

	MV	t-value	IV	t-value	Wald Test p-value	Adjusted R-Squared
			Panel A 1927 to 2005 with Variances in Logs			
1	-0.009	-0.278				-0.011
2			-0.056	-1.505		0.024
3	0.043	1.090	-0.104**	-2.406	0.047	0.032
			Panel B 1932 to 2005 with Variances in Logs			
4	0.029	1.436				0.007
5			-0.029	-0.701		-0.003
6					13.871	
	0.088***	3.717	-0.115***	-2.773	(0.001)	0.079
			Panel C 1932 to 2005 with Variances in Levels			
7	1.867	1.522				0.003
8			-1.031	-0.405		-0.009
9					5.767	
	4.337**	2.276	-3.988**	-1.960	(0.056)	0.031

Table 5 Control for Additional Predictive Variables

Note: The table reports OLS regression results of forecasting the one-quarter-ahead excess stock market return. MV is realized stock market variance and IV is the CAPM-based average idiosyncratic variance constructed using the 100 largest stocks. X stands for the forecasting variables listed in the first column. D12 is the dividend yield; E12 is the earning-price ratio; BM is the book-to-value ratio; TB1 is the yield on 1-year Treasury bonds; AAA is the yield on Aaa-rated corporate bonds; BAA is the yield on Baa-rated corporate bonds; LTY is the yield on long-term Treasury bonds; CAY is the consumption-wealth ratio proposed by Lettau and Ludvigson (2001); NTIS is net equity expansion; RFREE is the short-term interest rate; LINFL is the inflation rate; LTR is the return on long-term Treasury bonds; CORPR is the return on long-term corporate bonds; and CSP is the cross-sectional beta premium proposed by Polk et al (2006). Wald test is the test for the joint significance of MV and IV. We calculate the t-value using the Newey-West corrected standard error. ***, **, and * denote significant at the 1%, 5%, and 10% levels, respectively.

	MV	t-value	IV	t-value	X	t-value	Wald Test p-value	Adjusted R-Squared
D12	1.701**	2.380	-1.631***	-3.556	0.875	1.289	0.002	0.054
E12	2.159**	2.186	-1.735***	-3.261	0.396	1.778*	0.005	0.049
BM	1.752**	2.274	-1.679***	-3.427	0.069	1.549	0.003	0.063
TB1	2.198**	2.299	-1.911***	-4.044	-0.114	-0.633	0.000	0.040
AAA	2.295**	2.360	-1.991***	-4.245	0.023	0.125	0.000	0.040
BAA	2.307**	2.337	-2.040***	-4.133	0.095	0.503	0.000	0.040
LTY	2.280**	2.375	-1.974***	-4.267	-0.003	-0.018	0.000	0.040
CAY	2.496**	2.182	-1.262**	-2.207	1.439***	3.239	0.052	0.089
NTIS	1.522*	1.875	-1.930***	-4.123	0.302**	2.140	0.000	0.096
RFREE	2.188**	2.322	-1.901***	-4.117	-0.520	-0.707	0.000	0.041
INFL	2.162**	2.555	-2.019***	-3.926	-0.696	-0.744	0.000	0.046
LTR	2.272**	2.314	-2.061***	-4.439	0.253**	2.359	0.000	0.049
CORPR	2.283**	2.341	-2.065***	-4.427	0.259*	1.814	0.000	0.047
CSP	1.918**	2.421	-1.927***	-4.433	0.457	0.206	0.000	0.031

Table 6 Tests of Out-of-Sample Forecast Performance

Note: We assume that excess stock market returns are constant in the benchmark model and augment the benchmark model with realized stock market variance, MV, and the value-weighted idiosyncratic variance constructed from the 100 largest stocks, IV in row 1. We use the log transformations of these variables row 2. We report three out-of-sample forecast tests: (1) the mean-squared forecasting error (MSE) ratio of the augmented model to the benchmark model, / ; (2) the encompassing test ENC-NEW developed by Clark and McCracken (2001); and (3) the equal forecast accuracy test MSE-F developed by McCracken (1999). We use observations over the period 1927:Q1 to 1953:Q1 for the initial in-sample estimation and then generate forecasts recursively for stock returns over the period 1953:Q2 to 2005:Q4. The Asy. CV column reports the asymptotic 95 percent critical values provided by Clark and McCracken (2001) and McCracken (1999). The BS. CV column reports the empirical 95 percent critical values obtained from the bootstrapping, as in Lettau and Ludvigson (2001). In particular, we first estimate a VAR (1) process of excess stock market returns and its forecasting variables with the restrictions under the null hypothesis. We then feed the saved residuals with replacements to the estimated VAR system, of which we set the initial values to their unconditional means. The ENC-NEW and MSE-F statistics are calculated using the simulated data and the whole process is repeated 10,000 times.

	Models	MSE_A / MSE_B	ENC-NEW			MSE-F		
			Statistic	Asy. CV	BS. CV	Statistic	Asy. CV	BS. CV
1	C+MV +MV vs. C	0.95	12.66	2.09	2.92	10.79	1.52	1.11
2	C+LMV +LIV vs. C	0.98	13.58	2.09	2.99	5.064	1.52	1.36

Table 7 Alternative Measures of Stock Market Variance

Note: The table reports OLS regression results of forecasting the one-quarter-ahead excess stock market return. MV is realized stock market variance constructed using daily data in panel A; is realized stock market variance constructed using 5-minute data in panel B; and is implied variance constructed using options contracts on the S&P 100 index. IV is the CAPM-based average idiosyncratic variance constructed from the 100 largest stocks. The sample spans the period 1986:Q2 to 2004:Q4. Wald test is the test for the joint significance of MV and IV. We calculate the t-value using the Newey-West corrected standard error. ***, **, and * denote significant at the 1%, 5%, and 10% levels, respectively.

	MV	t-value	IV	t-value	Wald Test p-value	Adjusted R-Squared
			Panel B Daily Data			
1	0.387	0.668				-0.012
2			-1.278	-2.226		0.033
3	1.733**	2.592	-1.879***	-3.080	0.004	0.051
			Panel B 5-Minute Return Data			
4	1.213	0.552				-0.010
5	7.460***	2.825	-2.697***	-4.154	0.000	0.093
			Panel C Options-Implied Stock Market Variance			
6	1.995**	2.023				0.031
7	3.952***	3.713	-2.495***	-5.771	0.000	0.153

Table 8 Idiosyncratic Variance Constructed with Options-Implied Variance

Note: The table reports OLS regression results of forecasting the one-quarter-ahead excess stock market return. MV is the implied variance constructed using options contracts on the S&P 100 index and IV is the value-weighted average options-implied variances of common stocks. Wald test is the test for the joint significance of MV and IV. We calculate the t-value using the Newey-West corrected standard error. ***, **, and * denote significant at the 1%, 5%, and 10% levels, respectively.

	MV	t-value	IV	t-value	Wald Test p-value	Adjusted R-Squared
			Panel A Monthly Data: February 1996 to December 2005			
1	2.931**	1.997				0.020
2			-0.474	0.516		-0.001
3					9.081	
	5.284***	2.991	-1.400**	-2.207	(0.011)	0.056
			Panel B Quarterly Data: 1996:Q2 to 2005:Q4			
4	3.824***	3.059				0.106
5			-0.640	-1.392		-0.008
6					38.696	
	6.924***	6.052	-1.871***	-4.341	(0.000)	0.296

Table 9 Forecasting Stock Market Returns with Lagged Portfolio Returns

Note: We sort stocks equally into two portfolios by size, and then within each size portfolio we sort stocks equally into three portfolios by idiosyncratic variance. The portfolio returns are calculated using the value weight. We also construct a hedging portfolio, IVF, in a way similar to that of Fama and French (1996) in their construction of the value premium. In particular, for both small and big stocks, we calculate the return difference between the portfolio with low IV stocks and the portfolio with high IV stocks. IVF is then the equal-weighted difference across small and big stocks. MKT is the excess stock market return. We use the portfolio returns in the previous 12 quarters to forecast excess stock market returns in the following 4 quarters over the period 1950 to 2005. In parentheses we report the bootstrapped p-value. ***, **, and * denote significant at the 1%, 5%, and 10% levels, respectively.

		Panel A Lagged Returns on Portfolios Sorted by Size and IV			
		Low IV	RSQ	High IV	RSQ
1	Small	-0.169	0.010	-0.258**	0.055
		(0.320)		(0.048)	
2	Big	-0.260	0.016	-0.361**	0.076
		(0.273)		(0.021)	
		Panel B Lagged Returns on Risk Factors			
		MKT	RSQ	IVF	RSQ
3		-0.392	0.037	0.509**	0.075
		(0.121)		(0.030)	

Table 10 Cross-Sectional Regressions

Note: MKT is the excess stock market return; HML and SML are the value premium and the size premium, respectively, of the Fama and French (1996) 3-factor model; IVF is the return on a hedging portfolio that is long (short) in stocks with low (high) idiosyncratic variance. We test the asset pricing models using 25 Fama and French portfolios sorted by size and the book-to-market ratio over the period 1964:Q1 to 2005:Q4. Panel A reports the Fama and MacBeth (1973) cross-Sectional regression results. Panels B to D estimate the stochastic discount factor (SDF) models, in which SDF is a linear function of risk factors. For robustness, we use three different weighting matrices: the identity matrix in panel B; the inverted covariance matrix of the portfolio returns, as suggested by Hansen and Jagannathan (1997), in panel C; and Hansen's (1982) optimal weighting matrix in panel D. We test the model specifications using Jagannathan and Wang's (1996) distance measure (Dist) in panels B and C and Hansen's J-test in panel D. ***, **, and * denote significant at the 1%, 5%, and 10% levels, respectively.

	Const	MKT	HML	SMB	IVF	R^2	Dist (p-value)	J-test (p-value)
				Panel A Fama and MacBeth Regressions				
1	0.031**	0.008*	0.014***	-0.016		0.791		
	(2.538)	(1.722)	(3.021)	(-1.121)				
2	0.033**	0.009**		-0.018	0.020**	0.833		
	(2.658)	(2.061)		(-1.282)	(1.992)			
				Panel B SDF with Identity Weighting Matrix				
3		3.390***	5.998***	0.818***			0.045	
		(3.079)	(5.049)	(0.598)			(0.000)	
4		4.487***		8.983***	7.737***		0.034	
		(3.717)		(4.181)	(4.101)		(0.047)	
				Panel C SDF with HJ Weighting Matrix				
5		3.560***	5.890***	0.715			42.970	
		(3.331)	(5.208)	(0.531)			(0.003)	
6		4.658***		7.191***	6.824***		31.696	
		(4.387)		(4.196)	(5.971)		(0.053)	
				Panel D SDF with Optimal Weighting Matrix				
7		4.907***	7.830***	0.301				46.365
		(4.788)	(7.522)	(0.240)				(0.002)
8		6.124***		8.815***	9.147***			29.758
		(6.249)		(5.300)	(8.392)			(0.124)

Table 11 Forecasting One-Quarter-Ahead Stock Market Return with Realized Variance of IVF

Note: The table reports OLS regression results of forecasting the one-quarter-ahead excess stock market return. MV is realized stock market variance; IV is the CAPM-based average idiosyncratic variance constructed using the 100 largest stocks; and V_IVF is realized variance of the hedging portfolio that is long (short) in stocks with low (high) idiosyncratic variance. IV^+ is the residual from the regression of IV on a constant and V_IVF. Wald test is the test for the joint significance of the forecasting variables. We calculate the t-value using the Newey-West corrected standard error. ***, **, and * denote significant at the 1%, 5%, and 10% levels, respectively.

|	MV	t-value	V_IVF	t-value	IV^+	t-value	Wald Test p-value	Adjusted R-Squared
				Panel A 1927:Q1 to 2005				
1			-0.326	-1.238				-0.001
2	1.822*	1.768	-1.201***	-2.875			0.008	0.027
3	1.158**	1.981			-1.560*	-1.742	0.033	0.016
				Panel B 1927:Q1 to 1963:Q4				
4			-0.284	-1.068				-0.005
5	1.586	1.252	-1.038*	-1.854			0.100	0.014
6	1.098*	1.676			-2.277	-0.873	0.198	0.004
				Panel C 1964:Q1 to 2005:Q4				
7			-1.040	-1.559				0.003
8	2.403**	2.177	-2.092***	-2.968			0.012	0.034
9	1.756*	1.932			-1.027	-0.876	0.152	0.011

Table 12 Forecasting One-Quarter-Ahead Returns on the Hedging Portfolio

Note: The table reports OLS regression results of forecasting the one-quarter-ahead IVF—the return on the hedging portfolio that is long (short) in stocks with low (high) idiosyncratic variance. MV is realized stock market variance; IV is the CAPM-based average idiosyncratic variance constructed using the 100 largest stocks; and V_IVF is realized variance of IVF. Wald test is the test for the joint significance of the forecasting variables. We calculate the t-value using the Newey-West corrected standard error. ***, **, and * denote significant at the 1%, 5%, and 10% levels, respectively.

	MV	t-value	V_IVF	t-value	IV	t-value	Wald Test p-value	Adjusted R-Squared
			Panel A 1927:Q1 to 2005					
1	-0.676*	-1.940						0.006
2			0.560**	2.321				0.007
3	-1.679**	-2.244	1.366***	3.528			0.000	0.042
4					0.779**	2.260		0.011
5	-2.056***	-2.654			2.030***	3.777	0.001	0.059
			Panel B 1927:Q1 to 1963:Q4					
6	-0.256	-0.730						-0.004
7			0.514*	1.953				0.013
8	-1.068	-1.288	1.022**	2.074			0.029	0.039
9					0.771**	2.567		0.019
10	-1.709**	-2.013			2.045***	4.555	0.000	0.075
			Panel C 1964:Q1 to 2005:Q4					
11	-2.439**	-2.432						0.026
12			1.249	1.282				0.003
13	-3.728**	-2.414	2.887***	2.781			0.016	0.057
14					0.007	0.742		-0.001
15	-4.173**	-2.346			2.246**	2.225	0.046	0.060

Figure 1 Equal- (Thick Line) and Value-Weighted (Thin Line) Average IV

Panel A: 100 Largest Stocks
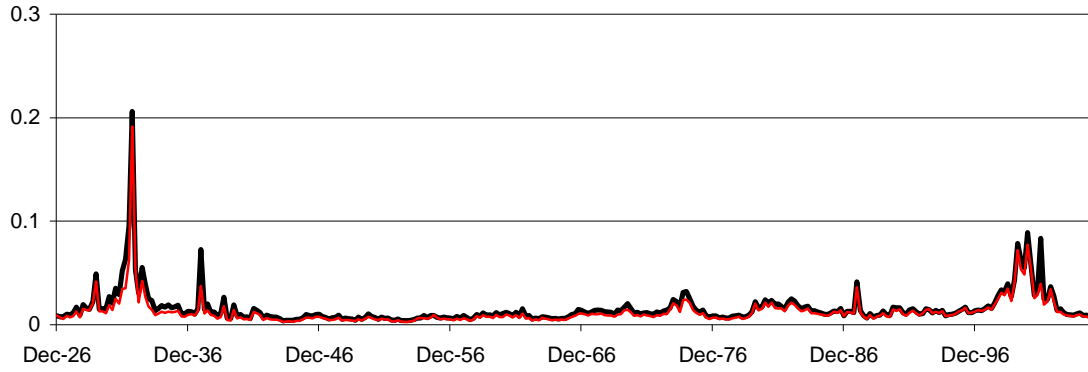
Panel B: 500 Largest Stocks
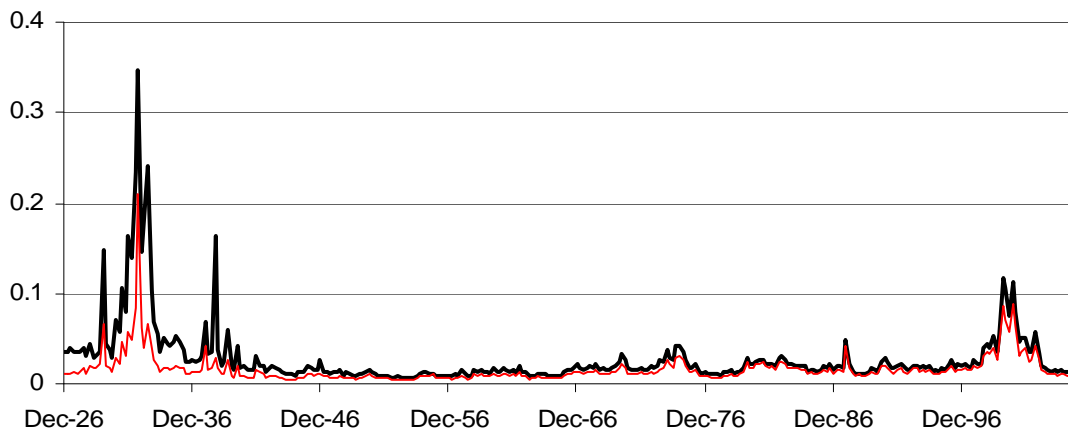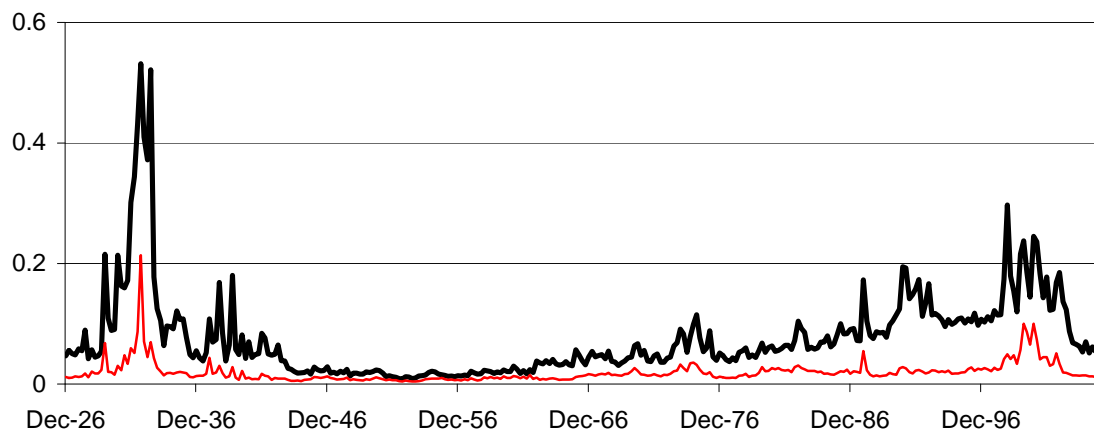

Panel C: All Stocks

Figure 2 Stock Market Variance (Thick Line, Left Scale) and
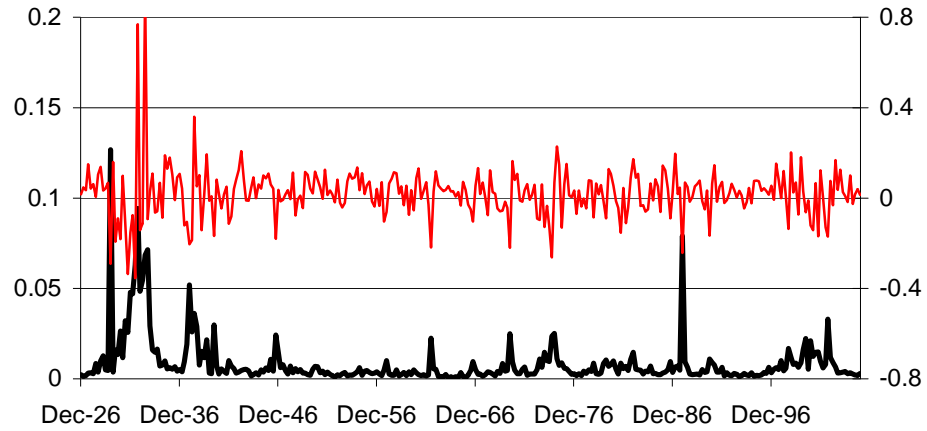Returns (Thin Line, Right Scale)

Figure 3 Realized Value Premium Variance (Thick Line, Left Scale) and Value-Weighted
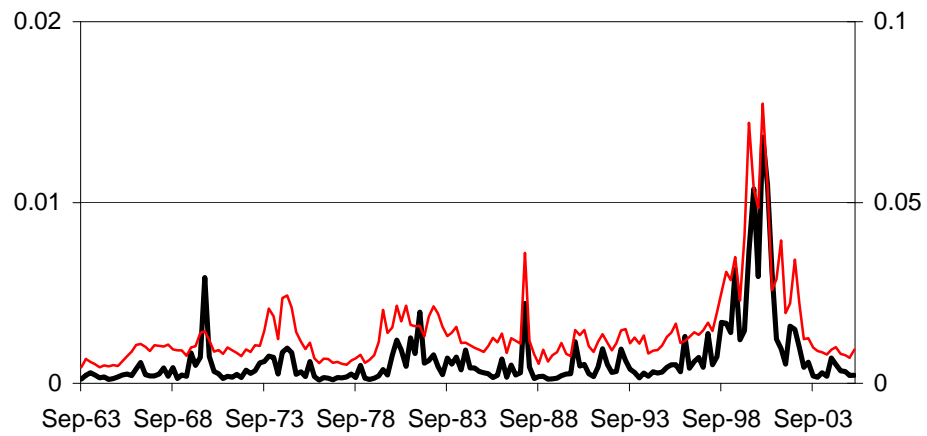Idiosyncratic Variance Constructed Using 100 Largest Stocks (Thin Line, Right Scale)
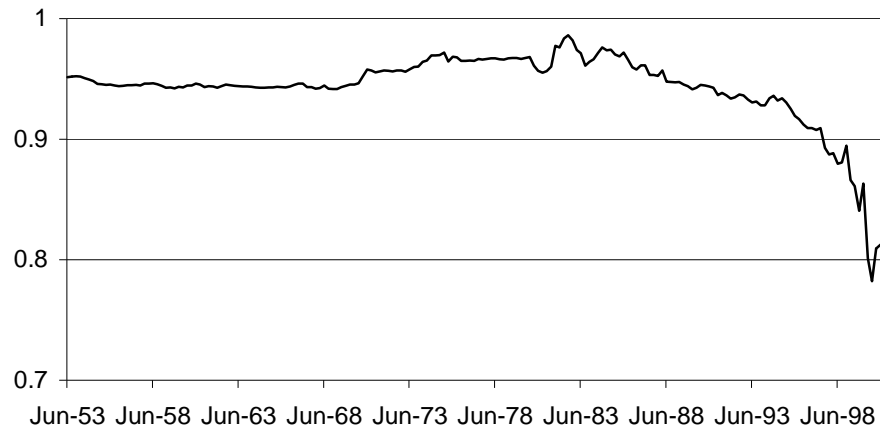
45

Figure 4 Recursive MSE Ratios

Figure 5 Differences in MSE between Benchmark Model and Forecasting Model
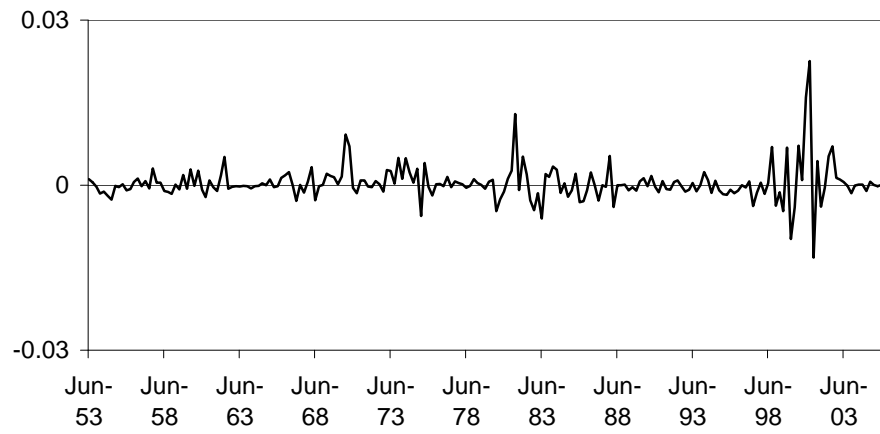

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Figure 6 Realized Stock Market Variance Constructed from 5-Minute (Thick Line) and Daily (Thin Line) Stock market Returns
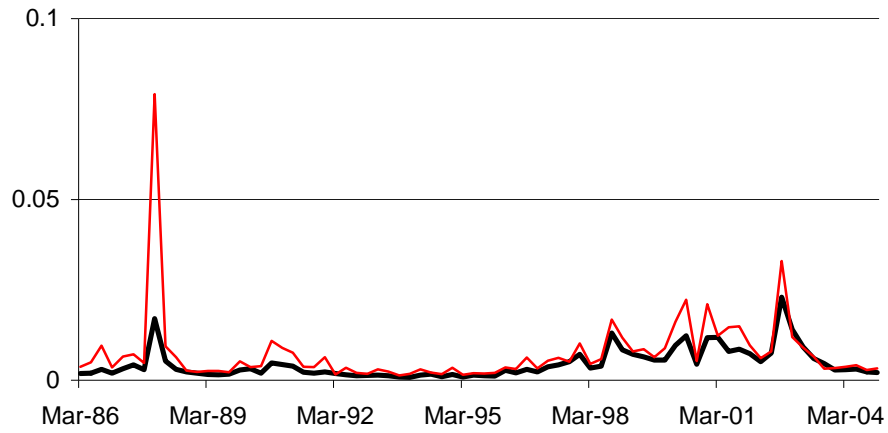

Figure 7 Value-Weighted Average IV Constructed from the 100 Largest Stocks (Thick Line, Left Scale) and 20 Industry Portfolios (Thin Line, Right Scale)