Understanding Stock Return Predictability

Hui Guo[*] Robert Savickas

Federal Reserve Bank of St. Louis George Washington University

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[*] Mailing Addresses: Department of Finance, University of Cincinnati, P.O. Box 210195, Cincinnati, OH 45221-0195, E-mail: hui.guo@uc.edu (Hui Guo, corresponding author); Department of Finance, George Washington University, 2023 G Street, N.W., Washington, DC 20052, E-mail: Savickas@gwu.edu (Robert Savickas). We thank Yakov Amihud, Torben Andersen, Andrew Ang, Geert Bekaert, John Campbell, Kalok Chan, Eric Chang, Michael Ferguson, FangJian Fu, Amit Goyal, Brian Hatch, Chunyang Huang, Stijn Van Nieuwerburgh, Jesper Rangvid, Steve Slezak, Samuel Thompson, Tuomo Vuolteenaho, Kuo-chiang Wei, Chu Zhang, Joe Zhang, Lu Zhang, Xiaoyan Zhang, and seminar participants at the University of Cincinnati, Loyola University in Chicago, the University of Hong Kong, the Hong Kong University of Science and Technology, Nang Nanyang Technological University, Singapore Management University, the 2007 D-CAF conference on stock return predictability, the 2007 European FMA meetings, and the 2007 FMA meetings for suggestions and comments. We also thank Amit Goyal for making his data available to us through his webpage.

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Abstract

Over the period 1927:Q1 to 2005:Q4, the average CAPM-based idiosyncratic variance (IV) and market variance jointly forecast stock returns. This result might reflect a close relation between IV and investment opportunities—a systematic risk factor omitted from CAPM. First, high lagged returns on high IV stocks predict low future returns on the market as a whole. Second, returns on a hedging portfolio that is long in stocks with low IV and short in stocks with high IV perform just as well as HML in explaining the cross-section of stock returns. Third, variance of the hedging portfolio or of HML is highly correlated with the average IV, and these three variables have very similar predictive power for stock returns.

Keywords: Stock Return Predictability, Average Idiosyncratic Variance, Stock Market Variance, Discount-Rate Shock, Cash-Flow Shock, CAPM, and ICAPM

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1. Introduction

There is an ongoing 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 show quite convincingly that there is little support for stock return predictability, especially in the out-of-sample context.

Cochrane (2006) points out that because dividend growth has negligible predictable variation and the dividend yield is quite volatile, the dividend yield must forecast stock market returns. Cochrane also 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. Moreover, 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.

This paper suggests that the variables used in the early studies have poor out-of-sample forecasting power possibly because they are not *direct* measures of the conditional equity premium. In particular, we propose a couple of predictive variables following the intuition of Merton's (1973) ICAPM, which stipulates that the conditional equity premium is a linear function of its (1) conditional variance and (2) conditional covariance with shocks to investment opportunities. Merton does not explicitly specify the state variables that describe investment opportunities. In the empirical analysis, we use the risk factors that appear to help explain the cross-section of stock returns as a proxy for the state variables. Fama (1991) has emphasized the importance of establishing a link between the time-series and cross-sectional stock return predictability. Thus, imposing the ICAPM restriction makes our specification less vulnerable to data mining, although it cannot be ruled out completely.

The value premium is perhaps 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 et al. (2004), Campbell and Vuolteenaho (2004), Petkova (2006), and Hahn and Lee (2006) provide some support for this conjecture. Consistent with the ICAPM interpretation, we find that realized variances of stock market returns and the value premium jointly forecast excess stock market returns over the period 1963:Q4 to 2005:Q4.[1] 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 for systematic risk in the pre-1963 sample.

Alternatively, we hypothesize that the CAPM-based idiosyncratic variance (IV) is a proxy for investment opportunities and thus forecasts stock returns. Appendix A shows that, in a two-factor ICAPM, the CAPM-based IV of stock *i* has two components:

$$IV_{i,t} = \beta_{i,DR}^2 \varepsilon_{DR,t}^2 + \varepsilon_{i,t}^2 , \quad (1)$$

where $\beta_{i,DR}$ is the loading on the hedging factor, $\varepsilon_{DR,t}$ is the shock to the hedging factor, and $\varepsilon_{i,t}$ is the true idiosyncratic shock. Campbell (1993) interprets $\varepsilon_{DR,t}$ as the shock to discount rates because in his model the time-varying equity premium is the main driver of changes in

[1] In this paper, we mainly focus on quarterly data instead of monthly data because Ghysels et al. (2005) argue that realized variance is a function of long distributed lags of daily returns. Nevertheless, we also find qualitatively similar results using monthly options-implied variances, which are arguably better measures of conditional variances than realized variances.

investment opportunities. Given that stock return predictability is the main focus of our study, Campbell's model provides a useful theoretical guidance for the empirical analysis in this paper.[2] We argue that stocks with high IV are more sensitive to the discount-rate shock than are stocks with low IV for at least three reasons. First, because an increase in the discount rate always leads an immediate fall in stock prices, $\beta_{i,DR}$ is negative in equation (1). Therefore, $\beta_{i,DR}^2 \varepsilon_{DR,t}^2$ is positively related to a stock's sensitive to the discount rate shock. Second, Cao et al. (2006) argue that firms with high IV are usually the firms with abundant growth options. This is possibly because, as emphasized by Cao et al., 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. And Berk, Green, and Naik (1999) show that discount rates have important effects on the valuation of growth options. Third, recent empirical studies, e.g., Pastor and Veronesi (2003), 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. These stocks are likely to have long durations and thus are sensitive to the discount-rate shock.[3]

We investigate the ICAPM implications of time-series stock return predictability in three ways. First, Guo and Savickas (2006) show that over the period 1963:Q4 to 2002:Q4, the value-weighted average IV forecasts stock returns when combined with realized stock market variance.

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[2] Campbell's (1993) model 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 et al. (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.

[3] 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.

Guo and Savickas (2007) find a similar result in G7 countries. One possible explanation is that the cross-sectional average of the second component in equation (1) is relatively stable over time and the average IV move closely along with the variance of the discount rate shock. Indeed, we show that over the period 1963:Q4 to 2005:Q4, the average IV and realized value premium variance are closely correlated with each other and have very similar forecasting power for stock returns.[4] Moreover, we provide out-of-sample tests for Guo and Savickas' results by showing that the average IV forecasts stock returns in a new subsample spanning the period 1927:Q1 to 1963:Q4 as well as in the longer sample spanning the period 1927:Q1 to 2005:Q4. Therefore, in contrast with the variables used in the earlier studies (see, e.g., Goyal and Welch (2006)), market variance and average IV have a rather stable relation with expected returns across time.

Second, if IV is a proxy for loadings on the discount-rate shock, high lagged returns on stocks with high IV should predict low future returns on the market as a whole because a positive shock to the discount rate leads stock prices to fall initially and to rise subsequently.[5] To address this issue, we follow Eleswarapu and Reinganum (2004) and use the returns on high IV stocks in the previous 12 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 low IV stocks.

Third, we construct a hedging portfolio that is long in stocks with low IV and short in stocks with high IV. The maintained hypothesis is that the portfolio return—dubbed as IVF—is a proxy for the discount-rate shock. Consistent with this conjecture, we find that lagged IVF is positively correlated with future stock market returns. Also, realized variances of stock market returns and IVF jointly have significant predictive power for excess stock market returns over the

[4] Note that Campbell and Vuolteenaho (2004) argue that the value premium is a priced risk factor because of its close relation with the discount-rate shock.

[5] We thank John Campbell for the suggestion of testing this ICAPM implication.

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 stock returns.

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—which, as mentioned above, is arguably a proxy for systematic risk—in explaining the cross-section of stock returns. By establishing a link between the time-series and cross-sectional stock return predictability, this evidence suggests that data mining is unlikely the main driver of our results.

The remainder of the paper is organized as follows. Section 2 provides some theoretical motivations and Section 3 discusses the data. We investigate the predictive power of the average IV in Section 4 and test the hypothesis that IV is a proxy for systematic risk in Section 5. Section 6 offers some concluding remarks.

2. Theoretical Motivations

In this section, we briefly explain the link between time-series and cross-sectional predictability in Campbell's (1993) ICAPM, which we exploit in our empirical analysis. In Campbell's model, there are two types of shocks to stock market returns—the shock to expected future cash flows and the shock to expected future stock market returns. Stock prices fall if there is a negative cash-flow shock or a positive discount-rate shock. However, the positive discount-rate shock is less risky than the negative cash-flow shock because the former also implies an improvement in investment opportunities—i.e., an increase in expected future stock returns. As a result, Campbell shows that the conditional excess stock market return, $E_t(R_{M,t+1}) - r_{f,t+1}$, is a linear function of its conditional variance, $\sigma^2_{M,t}$, and its conditional covariance with the discount-rate shock, $\sigma_{M,DR,t}$:

(2) $$E_t(R_{M,t+1}) - r_{f,t+1} = \gamma\sigma^2_{M,t} + (\gamma - 1)\sigma_{M,DR,t},$$

where γ is a measure of relative risk aversion.

Using the relation $\sigma_{M,DR,t} = \beta_{M,DR,t}\sigma^2_{DR,t}$, where $\beta_{M,DR,t}$ is the loading of stock market returns on the discount-rate shock, we can rewrite equation (2) as

(3) $$E_t(R_{M,t+1}) - r_{f,t+1} = \gamma\sigma^2_{M,t} + (\gamma - 1)\beta_{M,DR}\sigma^2_{DR,t},$$

where $\sigma^2_{DR,t}$ is conditional variance of the discount-rate shock. For simplicity, in equation (3), we assume that $\beta_{M,DR,t}$ is constant across time.[6] Note that $\beta_{M,DR}$ is negative because an increase in expected stock market returns leads to an immediate fall in stock prices and thus a negative stock market return. That is, in Campbell's (1993) ICAPM, the stock market serves as a hedge for changes in investment opportunities. The coefficient with stock market variance, γ, is positive if investors are risk averse. Also, if γ is greater than 1, as we find in this paper, the coefficient of $\sigma^2_{DR,t}$ should be negative. The latter result has an intuitive interpretation. Stock market variance includes variances of both the discount-rate shock and the cash-flow shock. Because the discount-rate shock is not as risky as the cash-flow shock, it is overpriced in the first right-hand-side term of equation (3). Therefore, the second right-hand-side term has a negative coefficient because it serves as a correction for the overpricing of the discount-rate shock in CAPM.

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[6] We primarily use the variance of the hedging risk factor (as in equation (3)) instead of the covariance between the hedging risk factor and the excess stock market return (as in equation (2)) to forecast stock returns. This is mainly because we interpret the average IV as a proxy for the variance of the hedging risk factor. Nevertheless, when using the value premium or IVF as a proxy for the hedging risk factor, we find qualitatively similar results by using both specifications. For brevity, the results for the covariance are not reported here but are available on request.

Recent studies, e.g., Campbell and Vuolteenaho (2004), Brennan et al. (2004), Petkova (2006), and Hahn and Lee (2006), find that over the post-1963 sample, the value premium is a proxy for shocks to investment opportunities. To investigate this possibility, we construct realized value premium variance using daily data obtained from Ken French at Dartmouth College for the period 1963:Q3 to 2005:Q4. We also construct realized stock market variance using the daily data obtained from CRSP (Center for Research in Security Prices) database.

Table 1 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 return returns, although the relation is statistically insignificant. Interestingly, when combined with realized stock market variance (MV), the coefficient of realized value premium variance remains negative and becomes significant at the 1% level. The negative coefficient is consistent with the implication of Campbell's (1993) ICAPM, in which the stock market serves as a hedge for changes in investment opportunities. Moreover, as expected, the relation between realized stock market variance and future stock market returns is significantly positive. Overall, the two variables account for about 4% of variation in stock market returns. Therefore, consistent with ICAPM, stock market returns are predictable by conditional variances of risk factors.

As explained in the introduction, the CAPM-based average IV can serve as a proxy for variance of the hedging factor omitted from CAPM. Consistent with this conjecture, Figure 1 shows that over the period 1963:Q3 to 2005:Q4, the value-weighted average IV constructed from the 100 largest stocks (thin line) move closely with realized value premium variance (thick line), with a correlation coefficient of about 88%. Moreover, Row 3, Table 1 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 the two variables contain similar information about future stock prices.

Before turning to the empirical results, we briefly explain the weak relation between the dividend yield and future stock returns. Appendix B shows that the log dividend yield is a linear function of conditional variances of stock market returns and discount-rate shocks:

(4) $$d_t - p_t = C + \begin{bmatrix} \gamma - \frac{1}{2} & (\gamma - 1)\beta_{M,DR} \end{bmatrix} (I - \rho A)^{-1} \begin{bmatrix} \sigma^2_{M,t} \\ \sigma^2_{DR,t} \end{bmatrix}.$$

Table B1 in Appendix B shows that the log dividend yield is indeed significantly related to stock market variance and proxies for the variance of the discount-rate shock. Equation (4) shows that the log dividend yield is a linear function of the conditional log equity premium, $\begin{bmatrix} \gamma - \frac{1}{2} & (\gamma - 1)\beta_{M,DR} \end{bmatrix} \begin{bmatrix} \sigma^2_{M,t} \\ \sigma^2_{DR,t} \end{bmatrix}$, as in equation (B2), only if $(I - \rho A)^{-1}$ is an identity matrix—a rather unrealistic assumption. Also, if $(\gamma - 1)\beta_{M,DR}$ is equal to zero or if $\sigma^2_{DR,t}$ and $\sigma^2_{M,t}$ are perfectly correlated with each other, equation (3) collapses to the conditional CAPM. In this case, the log dividend yield is proportional to the conditional equity premium because both variables are a linear function of conditional stock market variance. However, in this paper, we find that stock market variance alone does not forecast stock market returns because proxies for $\sigma^2_{DR,t}$ are also a significant determinant of the equity premium. Thus, in a multifactor model, the fact that the log dividend yield is an infinite sum of expected future stock returns does not necessarily imply that it is a measure of the conditional equity premium.

3. Data

We use the value-weighted stock market return obtained from CRSP as a proxy for aggregate stock 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 stock market returns and the risk-free rate.

Following Merton (1980), Andersen et al. (2003), and many others, realized stock market variance is the sum of squared daily excess stock market returns in a quarter:

$$(5) \qquad MV_t = \sum_{d=1}^{D_t} (ER_{M,d})^2 ,$$

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 et al. (1987), we also try to correct for the serial correlation in daily returns and find essentially the same results, which, for brevity, are not reported here.

Similar to Campbell et al. (2001), Goyal and Santa-Clara (2003), and Guo and Savickas (2006), the value-weighted average idiosyncratic variance is

$$(6) \qquad IV_t = \sum_{i=1}^{N_t} w_{i,t} \left[\sum_{d=1}^{D_{i,t}} e_{i,d}^2 + 2\sum_{d=1}^{D_{i,t}} e_{i,d} e_{i,d-1} \right] \text{ with } w_{i,t} = \frac{v_{i,t-1}}{\sum_{j=1}^{N_t} v_{j,t-1}} ,$$

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:

$$(7) \qquad e_{i,d} = ER_{i,d} - \widehat{\alpha} - \widehat{\beta} \cdot ER_{M,d} ,$$

where $ER_{i,d}$ is the excess return on stock *i* and $\widehat{\alpha}$ and $\widehat{\beta}$ 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) the 100 largest stocks, (2) the 500 largest stocks, and (3) all stocks.[7] We also construct the equal-weighted average IV assuming $w_{i,t} = \frac{1}{N}$ in equation (6). Our quarterly sample for the average IV spans the 1926:Q4 to 2005:Q4 period.[8]

Panel A, Figure 2 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 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 crash and the Great Depression. Panel B plots the average IV for the 500 largest stocks. We notice some difference between the equal-weighted and the value-weighted measures in the early period; however, they 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. In particular, consistent with Campbell et al. (2001), the equal-weighted average IV has trended upward since the late 1940s, although it decreased substantially at the end of our sample. However, the trend 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, as shown in

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[7] 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.

[8] Campbell and Thompson (2005) have emphasized that we should use CRSP total stock market return data, which are available only after 1926: The earlier return data are potentially unreliable because they are constructed with interpolated dividends.

equation (1), the average IV has two components—variance of the risk-factor omitted from CAPM and variance of 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 result also suggests 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 3 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 crash, the subsequent Great Depression, and the 1987 crash. To investigate whether the spikes have significant effects on our inference, we also use a log transformation for stock market variance and the average IV.

Table 2 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 find 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 2 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, as pointed out by Merton (1980), French et al. (1987), Andersen et al. (2003), and many others, they provide a good indication of future variances.[9] Thus, we primarily use lagged stock market variance and lagged average IV as proxies for conditional stock market variance and conditional variance of shocks to investment opportunities, respectively, and rewrite equation (3) as,

(8) $$R_{M,t+1} - r_{f,t+1} = \gamma MV_t + (\gamma - 1)\beta_{M,DR} IV_t + \varepsilon_{t+1}.$$

Equation (8) is our main empirical specification. Note that both forecasting variables in equation (8) are substantially less persistent than those 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 options contracts provides a better measure of conditional stock variance than lagged realized variance. Consistent with this finding, we show that using implied variance substantially enhances stock return predictability. Unfortunately, the data of implied variance are available for only a short sample period, and we have to mainly rely on realized variances in our empirical analysis.

4. Average Idiosyncratic Variance and Expected Stock Market returns

A. In-Sample Forecasts

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 will show later, we find essentially the same results using the value-weighted average IV

[9] Guo et al. (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, Guo et al. 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.

constructed from the 500 largest stocks or all stocks. We calculate the t-value using the Newey-West (1987) corrected standard error with 4 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 stock market variance by itself is statistically insignificant (row 1), and the average IV alone does not forecast stock market returns either (row 2). However, when we include both variables in the forecasting regression, the effect becomes statistically significant at the 5% and 1% levels for realized stock 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 the 1% 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 Campbell's (1993) ICAPM, there is a positive relation between conditional stock market return and variance. The coefficient of the average IV is negative, with a point estimate of –1.98. This result is consistent with the maintained hypothesis that the average IV is a proxy for the conditional variance of the discount-rate shock, which has a negative coefficient in equation (3) if γ —the coefficient of conditional stock market variance—is greater than 1.

The result that realized stock market variance and the average IV forecast stock market returns jointly but not individually reflects an omitted variable problem.[10] As we have explained in Section 2, stock market variance includes variances of both the cash-flow shock and the discount-rate shock. Because the discount-rate shock is not as risky as the cash-flow shock, the discount-rate shock is overpriced in CAPM. Therefore, the negative relation between stock

[10] Because of the correlation between realized stock 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 et al. (1980) confirms that multicollinearity is unlikely to plague our results.

market returns and the average IV—a proxy for the conditional variance of the discount-rate shock—serves as a correction for the overpricing.

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 first subsample, which has never been investigated before, provides an out-of-sample test for Guo and Savickas' (2006) evidence. The results from the first subsample are almost identical to those obtained from the full sample. When they enter the forecasting regression separately, neither realized stock market variance (row 4) nor the average IV (row 5) is a significantly predictor of stock market returns. However, the effect of these variables becomes significant at the 5% and 1% levels for stock market variance and the average IV, respectively, when both variables are included in the forecasting equation (row 6). Also, in the multivariate regression, while the coefficient of realized stock market variance is positive, it is negative for the average IV. Consistent with Guo and Savickas (2006), we also find essentially the same results for the second subsample. Note that the coefficients of both variables are quite stable in two subsamples. This result explains that, as we show below, realized stock market variance and the average IV have significant out-of-sample predictive power for stock returns.

B. Log Transformations of Variances

As shown in Figures 2 and 5, the average IV and realized stock 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 variables in the forecasting regression, and Table 4 shows that the results are qualitatively similar. For the full sample (panel A), the coefficients of log realized stock market variance (LMV) and log average IV (LIV) are significant at the 5% and 1% levels, respectively, when we include both variables in the forecasting regression (row 3). Also, while log realized stock market variance is positively related to future stock market returns, the relation is negative for log average IV. We also find qualitatively similar results in two subsamples.

C. Bootstrapping T-Statistics

Table 2 shows that both realized stock 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-statistics. In particular, we assume that stock 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 stock 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. Table 5 reports the p-value of the t-statistic obtained from the bootstrapping, which are consistent with those from the asymptotic distribution reported in parentheses. The small sample bias has small effects on our inference possibly because Table 2 shows that our forecasting variables are substantially less persistent than are those cautioned by Stambaugh (1999), for example, the dividend yield. For brevity, in the remainder of the paper, we use the asymptotic distribution of the t-statistic.

D. Alternative Measures of Average Idiosyncratic Variance

Because small stocks are more vulnerable to 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, Table 6 investigates some alternative measures of the average IV. We find essentially the same results using the value-weighted measures constructed from the 500 largest stocks (row 2) and all stocks (row 4). The results are somewhat mixed for the equal-weighted measures. We find essentially the same results for the equal-weighted measure constructed from the 100 largest stocks (row 1). This result should not be a surprise because panel A, Figure 2 shows that the equal-weighted and value-weighted measures for the largest 100 stocks are almost perfectly correlated with each other. However, the results are substantially weaker for the equal-weighted average idiosyncratic variance constructed from the 500 largest stocks (row 3) and all stocks (row 5). For robustness, we also repeat the above analysis using log transformations of both realized stock market variance and the average idiosyncratic variance, and find similar results (as shown in Table 7).

To summarize, as expected, the average IV constructed from large stocks performs better than the average IV constructed from small stocks in the forecasting regression. For brevity, in the remainder of the paper, we focus on the value-weighted idiosyncratic variance constructed from the 100 largest stocks.

E. Forecasting One-Year Ahead Excess Stock Market Returns

As a robustness check, we investigate whether realized stock market variance and the average IV at the last quarter of the previous year forecast the excess stock market return in the following year. Because we have considerably 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. Log realized stock market variance is also positively related to future stock returns; however, such a relation is statistically insignificant possibly because of the relative small sample size. Overall, the Wald test indicates that their joint predictive power is statistically significant at the 5% level.

Figures 2 and 5 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 shows that the both log realized stock 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 stock market variance is positive, it is negative for the average IV. Also, the adjusted R-squared increases sharply from 3.2% in panel A to 7.9% in panel B, indicating that the 1929 crash does have a confounding effect on our inference. Similarly, in panel C, we use the raw predictive variables to forecast stock returns over the period 1932 to 2005, and find qualitatively the same results.

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

F. Control for Other Predictive Variables

This subsection compares the forecasting power of realized stock 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 9 shows that the coefficient of realized stock 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).[11]

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.

G. *Out-of-Sample Forecasts*

As in Lettau and Ludvigson (2001) and others, 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 10 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 on average 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 substantially above the 5% asymptotic and bootstrap critical values. Therefore,

[11] 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.

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 10 reports the results for realized stock market variance and the average IV in logs, which are qualitatively the same as those reported in the first row.

Figure 4 plots the recursive MSE ratio of the forecasting model (in row 1 of Table 10) 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 stock market variance and the average IV jointly have strong 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 10), and we find that our results are not driven 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.

H. 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 stock market variance is substantially lower for 5-minute data than daily data at 1987:Q4.

Table 11 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 et al. (2003), we can estimate realized variance more precisely by using higher-frequency data.

In panel C of Table 11, 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 12 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 stock 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 12 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 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 stock 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 has been argued to be a proxy for 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 idiosyncratic variance is a proxy for risk.

A. Lagged Portfolio Returns and Expected Stock Market Returns

Equation (1) shows that the average IV is a proxy for the conditional variance of the discount-rate shock possibly because stocks with high IV are more sensitive to the discount-rate shock than are stocks with low IV. 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 (2004), 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 13 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 13 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 et al. (2006, 2007) 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 et al. (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 14 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 14 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, our results suggest that 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 15 investigates the time-series ICAPM implication that realized variance of IVF (V_IVF) forecasts 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. Moreover, the Wald test indicates that the joint predictive power of realized stock market variance and IVF is significant at the 5% level. We find qualitatively similar results in two subsamples (as shown in panels B and C), as well as by estimating a monthly bivariate GARCH model with IVF as the hedging factor. For brevity, the latter result is not reported here but is available on request.

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 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 a correlation coefficient of 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 15 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 is closely correlated with that of the conditional variance of shocks to the discount rate.

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 16, which also shows that the results are qualitatively similar by using the average IV as a proxy for the variance of the hedging factor. We also find qualitatively similar results for the value premium over the period 1964:Q1 to 2005:Q4; for brevity, this result is not reported here but is available on request.

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. One possible explanation is that IV is a proxy for loadings on the discount-rate shock, which is a systematic risk factor omitted from CAPM.

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 14 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. Thus, as shown in equation (1), if the cross-sectional average of the true idiosyncratic variance, $\varepsilon_{i,t}^{2}$, is relatively stable across time, the CAPM-based average IV is a proxy for the variance of the omitted risk factor. This interpretation seems to be consistent with the finding of a close relation between average IV and the variances of IVF and the value premium.

Second, as mentioned in introduction, Cao et al. (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 et al. (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.[12] 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

[12] The positive relation between the idiosyncratic risk and the stock price is consistent with the finding by Duffee (1995) and the results reported in Table B2.

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.[13] 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 et al. (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. 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 and Some Further Discussion

In this paper, we propose a couple of forecasting variables following the intuition of Campbell's (1993) ICAPM, in which conditional excess stock market returns are a linear function of conditional stock market variance and variance of shocks to the discount rate. While the discount-rate shock is not directly observable, we show that the average CAPM-based idiosyncratic variance is potentially a good proxy for variance of the hedging factor omitted from

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

CAPM. 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.

The discount-rate shock and the cash-flow shock have distinct effects on stock prices because we need to use two variances in the forecast of stock market returns. This result poses a challenge to the standard consumption-based CAPM with homogenous agents, in which the cash-flow shock and the discount-rate shock are perfectly correlated to each other. A successful model should allow some independence between the two types of shocks.[14] This boils down to the more fundamental question: Where does the discount-rate shock come from?

One possibility is that many financial market observers often relate the frequently observed boom-burst cycles of stock prices to variation in the market-wide liquidity. That is, a positive (negative) shock to liquidity will drive up (down) stock prices and thus lower (raise) expected future returns. Consistent with this interpretation, Guo and Savickas (2006) find that, when in conjunction with market variance, many standard measures of aggregate liquidity, e.g., trading volume and turnover, are negatively related to future stock market returns. This interpretation is potentially plausible because the market-wide liquidity does not need to move closely with fundamentals. In general equilibrium models, liquidity is priced because of market frictions, e.g., heterogeneous agents and borrowing constraints. Future research along this line should help us better understand the source of stock return predictability.

[14] Lettau and Wachter (2006) make a similar point when trying to explain the value premium using a partial equilibrium model.

Appendix A

If stock returns are predictable, we decompose the unexpected excess stock market return into the cash-flow shock ($N_{CF,t}$) and the discount-rate shock ($N_{DR,t}$):

(A1) $$ER_{M,t} - E_{t-1}(ER_{M,t}) = N_{CF,t} - N_{DR,t}\ .$$

In Campbell's (1993) ICAPM, discount rates are a measure of investment opportunities. If $R_{DR,t}$ is the return on a hedging portfolio, i.e., $R_{DR,t}$ has the perfect correlation with $N_{DR,t}$, we can write the ex-post excess return on any asset as

(A2) $$ER_{i,t} - E_{t-1}(ER_{i,t}) = \beta_{i,M}(ER_{M,t} - E_{t-1}ER_{M,t}) + \beta_{i,DR}(R_{DR,t} - E_{t-1}R_{DR,t}) + \varepsilon_{i,t}\ ,$$

where $\varepsilon_{i,t}$ is the idiosyncratic shock that is orthogonal to stock market returns and the discount-rate shock. Stock market returns and the discount-rate shock are correlated:

(A3) $$R_{DR,t} - E_{t-1}(R_{DR,t}) = \beta_{M,DR}(ER_{M,t} - E_{t-1}ER_{M,t}) + \varepsilon_{DR,t}\ .$$

We construct the CAPM-based idiosyncratic shock by regressing individual excess stock returns on excess stock market returns:

(A4) $$ER_{i,t} = \hat{\beta}_{i,t}ER_{M,t} + \eta_{i,t}\ ,$$

where $\hat{\beta}_{i,t}$ is the estimated loading on stock market returns in period *t*. It is then straightforward to show that realized CAPM-based IV of stock *i* is

(A5) $$IV_{i,t} = \eta_{i,t}^2 = \beta_{i,DR}^2\varepsilon_{DR,t}^2 + \varepsilon_{i,t}^2\ .$$

For ease of illustration, in equation (A5) we assume that realized IV for period *t* is the squared idiosyncratic shock of period *t*. However, in our empirical implementation, realized IV is the sum of squared daily idiosyncratic shocks in period *t*.

Appendix B

We follow Campbell and Shiller (1988) and write the log dividend yield, $d_t - p_t$, as

(B1) $$d_t - p_t = -\frac{\kappa}{1-\rho} + E_t \sum_{j=0}^{\infty} \rho^j (r_{M,t+j+1} - \Delta d_{t+j+1}),$$

where $-\frac{\kappa}{1-\rho}$ is a constant, $r_{M,t+j+1}$ is the log stock market return, and Δd_{t+j+1} is the dividend growth rate. Using the relation $E_t(R_{M,t+1}) = E_t(r_{M,t+1}) + \frac{1}{2}\sigma^2_{M,t}$, we can rewrite equation (3) as

(B2) $$E_t(r_{M,t+1}) - r_{f,t+1} = (\gamma - \frac{1}{2})\sigma^2_{M,t} + (\gamma - 1)\beta_{M,DR}\sigma^2_{DR,t}.$$

For simplicity, we assume that the conditional variances $\sigma^2_{M,t}$ and $\sigma^2_{DR,t}$ follow a joint VAR(1) process:

(B3) $$\begin{bmatrix} \sigma^2_{M,t+1} \\ \sigma^2_{DR,t+1} \end{bmatrix} = A_0 + A \begin{bmatrix} \sigma^2_{M,t} \\ \sigma^2_{DR,t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t+1} \\ \varepsilon_{2,t+1} \end{bmatrix}.$$

We also assume that the expected dividend growth and the risk-free rate are constant. Note that these three assumptions should not affect our main results in any qualitative manner. Then it is straightforward to show that

(B4) $$d_t - p_t = C + \begin{bmatrix} \gamma - \frac{1}{2} & (\gamma - 1)\beta_{M,DR} \end{bmatrix} (I - \rho A)^{-1} \begin{bmatrix} \sigma^2_{M,t} \\ \sigma^2_{DR,t} \end{bmatrix},$$

where C is a collection of the constant terms. Table B1 provides empirical evidence of equation (B4).

Table B1 Realized Variances of Risk Factors and the Dividend Yield

Note: The table reports OLS regression results of the dividend yield on variances of risk factors. MV is realized stock market variance; IV is the CAPM-based average idiosyncratic variance constructed using the 100 largest stocks; V_IVF is realized variance of the hedging portfolio that is long (short) in stocks with low (high) idiosyncratic variance; and V_HML is realized value premium variance. V_HML is available over the period 1963:Q4 to 2005:Q4; and all the other variables are available over the period 1926:Q4 to 2005:Q4. 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_IVF	t-value	V_HML	t-value	Adjusted R-Squared
1	0.319***	7.122	-0.514***	-5.130					0.333
2	0.195***	3.567			-0.132**	-2.017			0.074
3	0.152***	2.745					-0.283***	-3.517	0.203

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Table 1 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 2 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 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-Quarter-Ahead Excess Stock Market Return Using Log Variances

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

	LMV	t-value	LIV	t-value	Wald Test p-value	Adjusted R-Squared
			Panel A 1927:Q1 to 2005:Q4			
1	0.009	0.945				0.002
2			-0.013	-1.170		0.002
3	0.028**	2.246	-0.040***	-3.582	0.002	0.027
			Panel B 1927:Q1 to 1963:Q4			
4	0.007	0.487				-0.004
5			-0.012	-0.576		-0.003
6	0.037*	1.843	-0.057**	-2.383	0.049	0.018
			Panel C 1964:Q1 to 2005:Q4			
7	0.010	1.254				0.003
8			-0.008	-0.640		-0.003
9	0.029***	2.695	-0.039**	-2.393	0.021	0.026

Table 5 Bootstrapping t-Values: 1927:Q1 to 2005:Q4

Note: The table reports the p-value of the t-statistic obtained from the bootstrapping for the regression of forecasting the one-quarter-ahead excess stock market return. For comparison, we also report the asymptotic p-value in parentheses. In particular, we assume that excess stock market returns (RET), realized stock market variance (MV), and the CAPM-based idiosyncratic variance (IV) follow a joint VAR(1) process with the restrictions under the null hypothesis that the expected excess stock 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. ***, **, and * denote significant at the 1%, 5%, and 10% levels, respectively, according to the empirical distributions.

	MV	p-value	IV	p-value	Adjusted R-Squared
			Panel A Variances in Levels		
1	2.284**	0.026	-1.977***	0.000	
		(0.010)		(0.000)	0.043
			Panel B Variances in Logs		
2	0.028**	0.019	-0.040***	0.000	
		(0.013)		(0.000)	0.027

Table 6 Different Measures of Idiosyncratic Variance: 1927:Q1 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 and IV is the CAPM-based average idiosyncratic variance. 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
			Equal-Weighted 100 Largest Stocks			
1	2.411***	2.717	-1.718***	-3.663	0.001	0.041
			Value-Weighted 500 Largest Stocks			
2	2.500***	2.723	-1.755***	-4.619	0.000	0.039
			Equal-Weighted 500 Largest Stocks			
3	1.213*	1.893	-0.130	-0.299	0.053	0.007
			Value-Weighted All Stocks			
4	2.235**	2.416	-1.411***	-3.899	0.000	0.033
			Equal-Weighted All Stocks			
5	0.991**	2.066	-0.014	-0.111	0.117	0.006

Table 7 Different Measures of Idiosyncratic Variance in Logs: 1927:Q1 to 2005:Q4

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

	LMV	t-value	LIV	t-value	Wald Test p-value	Adjusted R-Squared
			Equal-Weighted 100 Largest Stocks			
1	0.032***	2.723	-0.047***	-3.877	0.000	0.030
			Value-Weighted 500 Largest Stocks			
2	0.030***	2.664	-0.042***	-3.603	0.001	0.023
			Equal-Weighted 500 Largest Stocks			
3	0.021**	2.279	-0.020	-1.064	0.074	0.005
			Value-Weighted All Stocks			
4	0.024**	2.153	-0.032	-3.077***	0.005	0.016
			Equal-Weighted All Stocks			
5	0.012	1.357	-0.005	-0.701	0.259	0.000

Table 8 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 9 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 10 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 Statistic	ENC-NEW Asy. CV	ENC-NEW BS. CV	MSE-F Statistic	MSE-F Asy. CV	MSE-F 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 11 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 12 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 13 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 14 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 15 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 16 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: Realized Value Premium Variance (Thick Line, Left Scale) and Value-Weighted Idiosyncratic Variance Constructed Using 100 Largest Stocks (Thin Line, Right Scale)

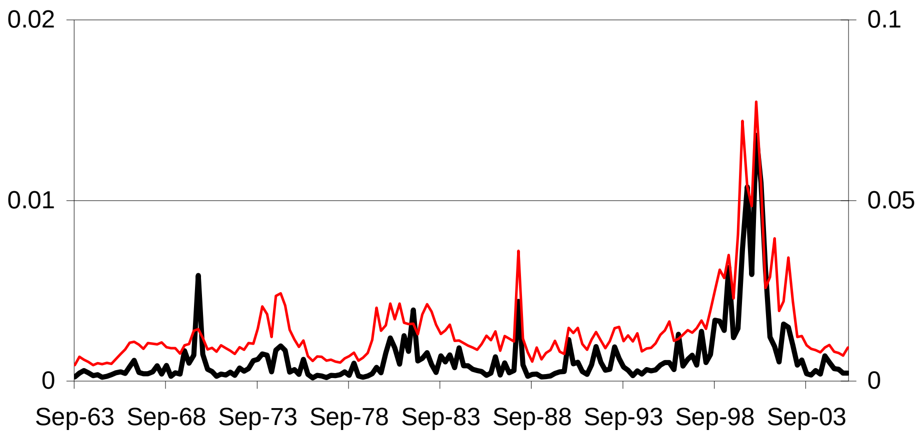
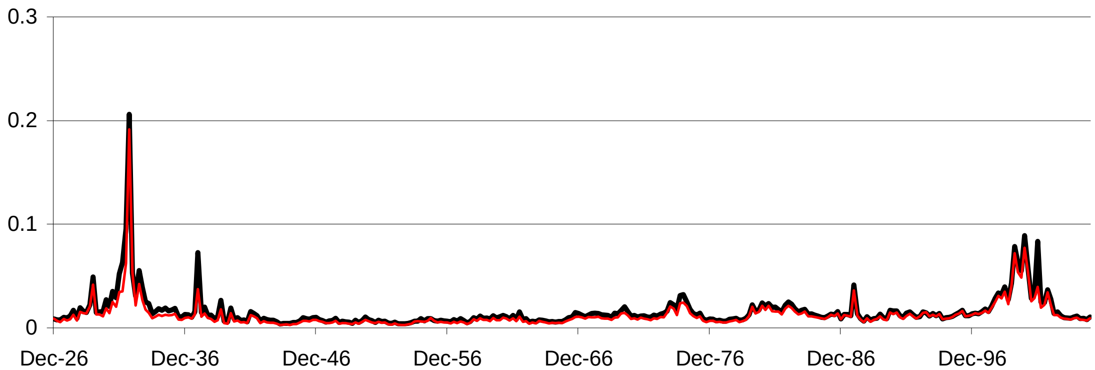
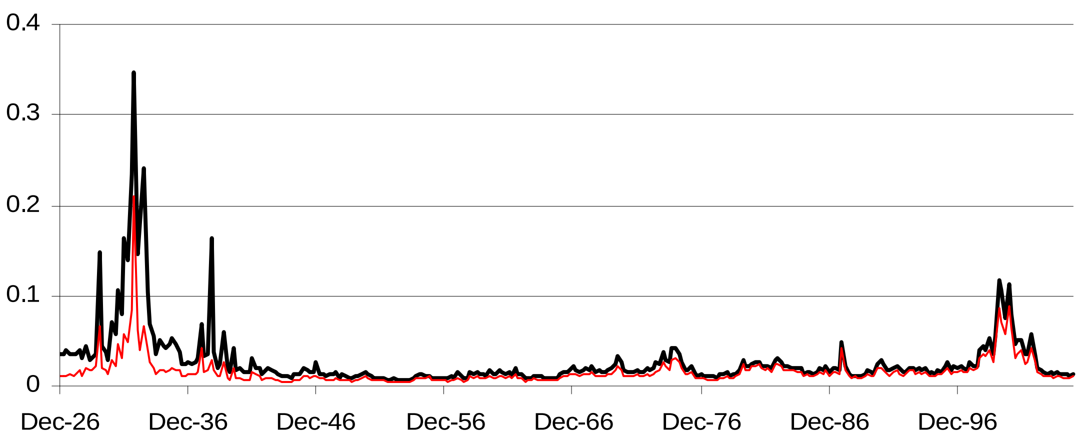


Figure 2 Equal- (Thick Line) and Value-Weighted (Thin Line) Average IV

Panel A: 100 Largest Stocks



Panel B: 500 Largest Stocks



Panel C: All Stocks

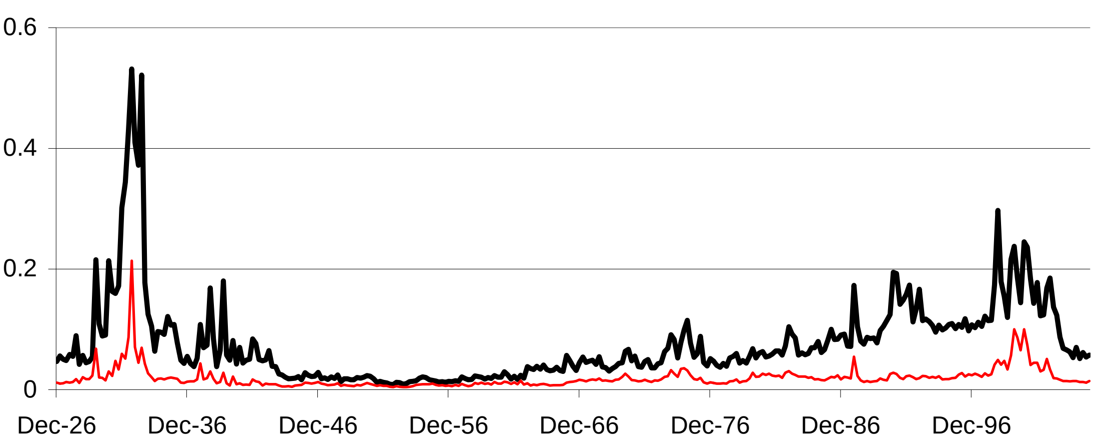


Figure 3 Stock Market Variance (Thick Line, Left Scale) and Returns (Thin Line, Right Scale)

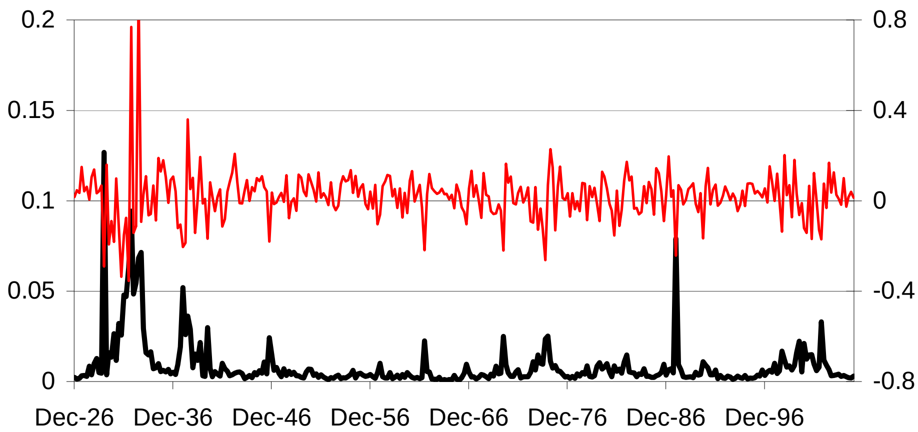


Figure 4 Recursive MSE Ratios

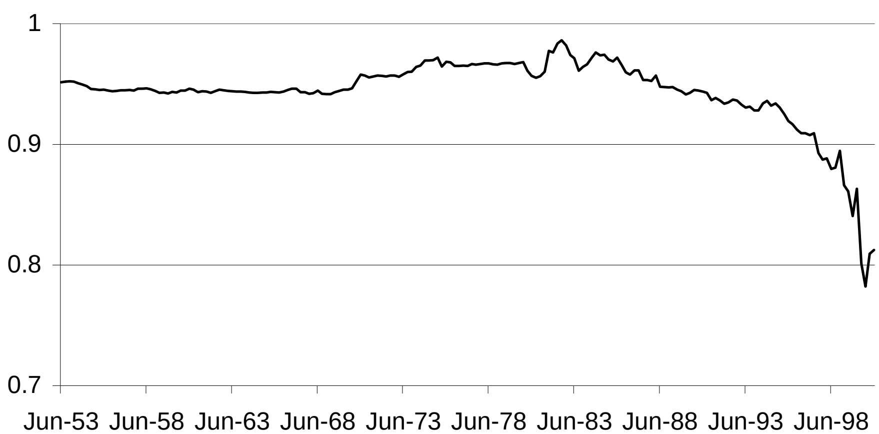


Figure 5 Differences in MSE between Benchmark Model and Forecasting Model

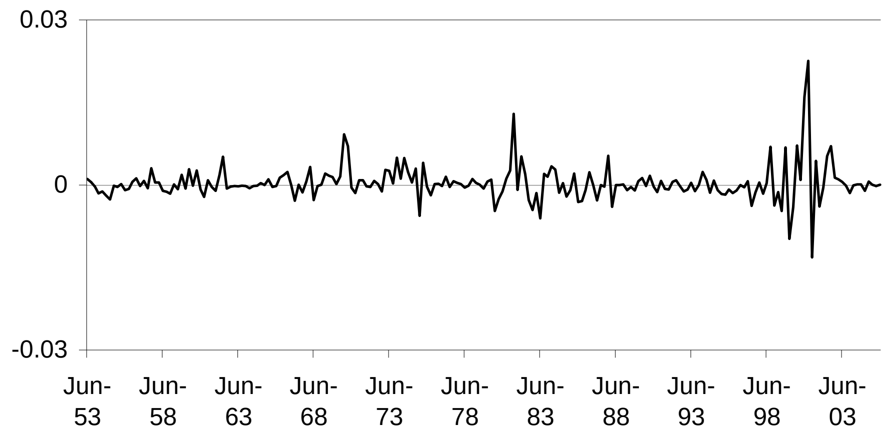


Figure 6 Realized Stock Market Variance Constructed from 5-Minute (Thick Line) and Daily (Thin Line) Stock market Returns

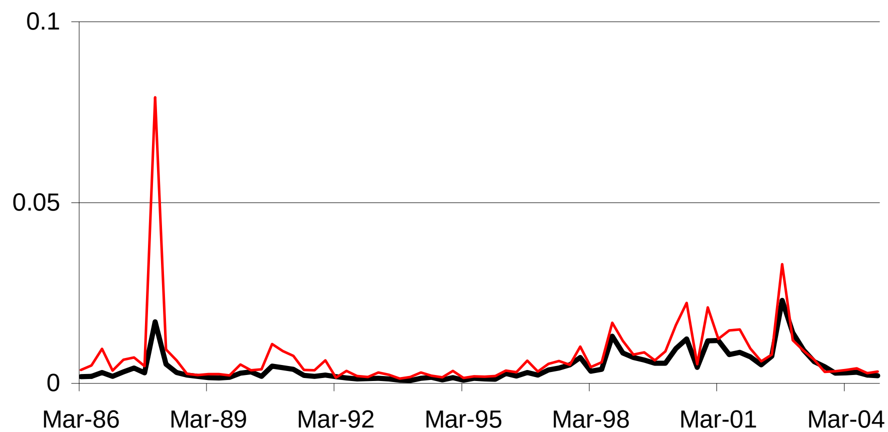


Figure 7 Value-Weighted Average IV Constructed from the 100 Largest Stocks (Thick Line, Left Scale) and 20 Industry Portfolios (Thin Line, Right Scale)