Relation between Time-Series and Cross-Sectional Effects of Idiosyncratic Variance on Stock Returns

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Abstract

Consistent with the post-1962 U.S. evidence by Ang, Hodrick, Xing, and Zhang (2006), we find that stocks with high idiosyncratic variance (IV) have low CAPM-adjusted expected returns in both pre-1962 U.S. and modern G7 data. We also test the conjecture that IV is a proxy of systematic risk in three ways. First, the return difference between low and high IV stocks—that we dub as IVF—is priced in the cross-section of stock returns. Second, loadings on lagged market variance and lagged average IV account for a significant portion of variation in average returns on portfolios sorted by IV. Third, the variance of IVF is closely correlated with average IV, and they have similar explanatory power for the time-series and cross-sectional stock returns.

Keywords: stock return predictability, average idiosyncratic variance, stock market variance, cross-section of stock returns, value premium, and CAPM

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I. Introduction

Recent studies indicate that realized idiosyncratic variance (IV) forecasts stock returns in two ways. First is the *cross-sectional* effect. Easley, Hvidkjaer, and O'Hara (2002) and Ang, Hodrick, Xing, and Zhang (2006) find that high IV stocks have lower CAPM-adjusted expected returns than do low IV stocks in the post-1962 U.S. CRSP (Center for Research in Security Analysis) data. Second is the *time-series* effect. Guo and Savickas (2008) show that when in conjunction with stock market variance (MV), value-weighted average IV (VWAIV) correlates negatively with future market returns in G7 countries. These authors also uncover a positive relation between MV and expected market returns.

The negative relation between IV and expected stock returns appears to be puzzling. In particular, some early authors, e.g., Levy (1978), Merton (1987), and Malkiel and Xu (2002), have argued that the relation should be *positive*. Because existing studies do not provide a conclusive explanation, there is a concern that the negative effect of IV on expected stock returns is specific to the post-1962 U.S. sample. As a robustness check, we revisit the issue using two previously unexplored datasets: (1) the newly available pre-1962 CRSP data of U.S. and (2) the Datastream data of G7 countries. We find that the negative cross-sectional IV effect is a pervasive phenomenon and thus cannot be simply attributed to data snooping.

Our empirical findings also suggest that the IV effects might reflect systematic risk. The return difference between low and high IV stocks—that we dub as IVF—is significantly priced in the cross-section of stock returns. Realized variances of market returns and of IVF jointly forecast stock returns across time; interestingly, loadings on the two variables have significant explanatory power for the average returns on portfolios sorted by IV. Moreover, the variance of IVF is closely correlated with VWAIV, and the two variables have similar time-series and cross-sectional explanatory power for stock returns. The close link between time-series and cross-sectional return predictability suggests a risk-based explanation of the IV effects.

We explore further a tentative explanation of the IV effects based on the conjecture that high IV stocks are more sensitive to discount-rate shocks than are low IV stocks. The conjecture is built on two arguments. First, recent empirical studies have documented a close relation between IV and investment opportunities. Cao, Simin, and Zhao (2008), for example, find that firms with high IV are usually the firms with abundant growth options. Similarly, Pastor and Veronesi (2003) and Wei and Zhang (2006) show that high IV stocks tend to be young and small; have a low book-to-market equity ratio, low returns on equity, and high volatility of profitability; and pay no dividends. Second, the seminal work by Berk, Green, and Naik (1999) suggests that the valuation of growth options depends crucially on discount rates because unlike assets in place, they tend to generate cash flows in the distant future. Following this intuition, Lettau and Wachter (2007) develop a partial equilibrium model, in which growth stocks are more sensitive to discount-rate shocks than are value stocks because the former have longer durations.[1] We find that, consistent with the maintained hypothesis, returns on high IV stocks are negatively related to future market returns, while the predictive power is negligible for low IV stocks. Therefore, high IV stocks have lower expected returns than do low IV stocks possibly because, as emphasized by Campbell (1993), discount-rate shocks are not as risky as cash-flow shocks. IVF is priced in the cross-section of stock returns possibly because of its relation with discount-rate shocks—e.g., IVF has significant predictive power for market returns.

The potential explanation for the cross-sectional IV effect is related to that proposed by Campbell and Vuolteenaho (2004) for the B/M effect—stocks with high B/M (value stocks) have higher expected returns than stocks with low B/M (growth stocks) because the latter are more

[1] In Lettau and Wachter (2007), growth stocks refer to stocks with a low book-to-market (B/M) equity ratio and value stocks have a high B/M ratio.

sensitive to discount-rate shocks. We thus expect that the IV effect should be closely related to the B/M effect. Consistent with this conjecture, we document a close relation between IVF and HML—the return difference between value stocks and growth stocks—in the post-1962 sample, with a correlation coefficient of about 50%. Moreover, the two variables have similar explanatory power for the Fama and French (1996) 25 portfolios sorted by size and B/M.

Our results suggest that IVF might be correlated with systematic risk; however, it is important to note that our tests of the risk-based interpretation are only indirect because hedging risk factors, e.g., discount rates, are unobservable. Nevertheless, our findings shed light on two existing alternative explanations. The first hypothesis is based on limits of arbitrage—IV is a proxy for the divergence of opinion (e.g., Shalen (1993)), which leads a stock to be over-valued initially and to suffer capital losses eventually when short-sales constraints are binding (Miller, 1977).[2] Consistent with this hypothesis, Bali, Scherbina, and Tang (2009) show that a large unexpected increase in idiosyncratic volatility, which is often driven by major corporate news, tends to raise the divergence of opinions as measured by the effective bid-ask spread. The second hypothesis—as proposed by Jiang, Xu, and Yao (2009)—is based on irrational pricing that builds on two arguments. First, firms with poor prospect of future earnings have high IV because they tend to disclose less information. Second, investors underreact to earnings information contained in IV. Neither hypothesis, however, explains the close link between the time-series and cross-sectional IV effects, as we document in this paper.

Fu (2009) uncovers a *positive* relation between expected stock returns and conditional IV constructed using the EGARCH model. His results differ from those by Ang, Hodrick, Xing,

[2] The empirical evidence on Miller's (1977) hypothesis is mixed, however. Some authors, e.g., Chen, Hong, and Stein (2002), Diether, Malloy, and Scherbina (2002), Asquith, Pathak, and Ritter (2005), and Boehme, Danielsen, and Sorescu (2006), document a negative relation between proxies of the divergence of opinion and expected stock returns, especially for stocks that are likely to have binding short-sales constraints. Other authors, e.g., Doukas, Kim, and Pantzalis (2006), find little support for Miller's hypothesis.

and Zhang (2006) possibly because, as argued by Chua, Goh, and Zhang (2009), conditional IV (as used in Fu) and realized IV (as used in Ang, Hodrick, Xing, and Zhang) are measures of different risks. Goyal and Santa-Clara (2003) find a positive relation between equal-weighted average IV and future market returns in monthly data; however, Bali, Cakici, Yan, and Zhang (2005) show that their results are sensitive to the weighting scheme and the slight extension of the sample period. In a concurrent paper, Ang, Hodrick, Xing, and Zhang (2009) investigate the cross-sectional IV effect in G7 countries and find results qualitatively similar to ours. The focus of their paper is different, however. We investigate whether the IV effects reflect systematic risk, while Ang, Hodrick, Xing, and Zhang test whether the cross-sectional IV effect is related to the known cross-sectional patterns. Moreover, unlike this paper, Ang, Hodrick, Xing, and Zhang do not analyze the pre-1962 U.S. data.

The remainder of the paper is organized as follows. We explain the main refutable implications about the relation between the time-series and cross-sectional IV effects in Section II. We discuss data in Section III. We present the empirical results using U.S. data in Section IV and using international data in Section V. We conduct diagnostic tests in Section VI and offer some concluding remarks in Section VII.

II. Time-Series and Cross-Sectional IV Effects: Some Refutable Implications

Ang, Hodrick, Xing, and Zhang (2009) find that, as we confirm in this paper, there is strong comovement in IVF across countries. These authors suggest that broad, not easily diversifiable factors may lie behind this phenomenon.[3] Similarly, Guo and Savickas (2008) document strong comovement in VWAIV across G7 countries. Moreover, these authors find that loadings on lagged VWAIV and lagged MV help explain the cross-section of stock returns

[3] This argument is similar to that used by Fama and French (1996) for the ICAPM interpretation of HML, which appears to be a pervasive phenomenon because it is related to many cross-sectional patterns.

on portfolios sorted by B/M. In this paper, we hypothesize that the IV effects reflect systematic risk and test the hypothesis in three ways.

- IVF helps explain the cross-section of stock returns.
- Conditional variance of IVF forecasts stock returns across time when in conjunction with conditional market variance. Moreover, loadings on conditional variances of market returns and of IVF help explain the cross-section of stock returns.
- VWAIV is closely correlated with conditional variance of IVF; and the two variables have similar explanatory power for both time-series and cross-sectional stock returns.

Because we construct IVF using portfolios sorted by IV, the fact that IVF is priced in the portfolios sorted by IV does not necessarily imply that IVF reflects systematic risk. It is, however, not obvious why such a mechanical link explains that VWAIV or the variance of IVF is also significantly priced.

Recent studies, e.g., Cao, Simin, and Zhao (2008), Pastor and Veronesi (2003), and Wei and Zhang (2006), find that firms with high IV tend to have abundant growth options. Because stocks with abundant growth options have cash flows in the distant future and thus have long durations, high IV stocks are likely to be especially sensitive to discount-rate shocks—the hedging risk factor in Campbell’s (1993) ICAPM. This conjecture is similar to that proposed by Campbell and Vuolteehano (2004) for the B/M effect. Given the close relation between IV and B/M in data (e.g., Pastor and Veronesi (2003)), it seems interesting to explore the interpretation for the IV effects in the context of discount-rate shocks. In this paper, we provide tentative tests of this conjecture in three ways.

- If, as hypothesized, high IV stocks are especially sensitive to discount-rate shocks, their returns should be negatively correlated with future market returns. In contrast, the predictive power should be much weaker for low IV stocks.[4]
- Using IVF as a proxy for the hedging risk factor helps uncover a positive risk-return relation.
- We expect a strong relation between IVF and HML; and the two variables should have similar explanatory power for the cross-section of stock returns.

Note that the refutable implications proposed in this section provide only necessary but not sufficient conditions for the rational pricing interpretation of the IV effects. Nevertheless, they help distinguish alternative hypotheses, for example, they pose a challenge to explanations based on data mining or irrational pricing.

III. Data

We use stock return data from CRSP for the U.S. over the period January 1926 to December 2005 and from the Datastream for G7 counties—Canada, France, Germany, Italy, Japan, U.K., and U.S.—over the period January 1973 to December 2003. Unless otherwise indicated, all returns are denominated in local currencies. We obtain the monthly risk-free rate data from CRSP for the U.S. and from IFS (the International Financial Statistics) for the other G7 countries. Because the risk-free rate is available only at the monthly frequency, we assume that the daily risk-free rate is constant within a month and compounds to the monthly risk-free rate. The daily excess stock return is the difference between the daily stock return and the daily risk-free rate.

We follow Ang, Hodrick, Xing, and Zhang (2006) in the construction of portfolios sorted by the CAPM-based IV. At the beginning of each month, we calculate realized IV, which is the

[4] We thank John Campbell for suggesting this test.

sum of squared daily CAPM-based idiosyncratic shocks in the previous month. Stocks are then sorted equally by IV into quintile portfolios, for example, the first quintile includes stocks with the lowest IV and the fifth quintile includes stocks with the highest IV. The portfolios are held for one month and are rebalanced at the beginning of the next month, and so on. Unless otherwise indicated, we follow Ang, Hodrick, Xing, and Zhang and use value-weighted portfolio returns throughout the paper for the reasons described below.

Both the time-series and cross-sectional IV effects are found to be sensitive to weighting schemes. Guo and Savickas (2008) find that the equal-weighted average IV does not forecast market returns even when in conjunction with MV. Bali and Cakici (2008) note that the cross-sectional IV effect attenuates substantially if using equal weighting scheme; in this paper, we find qualitatively similar results using both the early U.S. data and international data. The difference between equal and value weighting schemes may reflect two distinct effects of IV on stock returns. First, as we hypothesize in this paper, high IV stocks tend to have abundant growth options and thus are sensitive to discount-rate shocks. This hypothesis implies a negative relation between IV and CAPM-adjusted expected returns. Second, small stocks also tend to have higher IV than do large stocks because the former are less illiquid. This hypothesis implies a positive relation between IV and expected returns (e.g., Amihud and Mendelson (1989) and Spiegel and Wang (2005)). As we show in next section (Tables 1 and 3), the negative cross-sectional IV effect is noticeably weaker for small stocks than for big stocks. Therefore, the equal weighting scheme attenuates the negative relation between IV and expected returns possibly because it gives excess emphasis to small illiquid stocks. Because our major concern is whether the time-series and cross-sectional IV effects reflect intertemporal pricing, we mainly use the value weighting scheme in this paper unless otherwise indicated.

We aggregate IV across the 500 largest common stocks with value weighting to construct VWAIV; the results are qualitatively similar by using all CRSP common stocks. Following Merton (1980) and Andersen, Bollerslev, Diebold, and Labys (2003), MV is the sum of squared daily excess stock market returns in a given period. We confirm that MV and VWAIV jointly have significant predictive power for excess market returns in both the modern and long U.S. samples. For brevity, we do not report these results here but they are available on request.

Following the procedure recommended by Guo and Savickas (2008), we have imposed some filters for the Datastream data for potential errors. Section V shows that for the U.S., the imposition of these filters produces the cross-sectional IV effect qualitatively similar to that obtained from the CRSP data. This result confirms the appropriateness of the following filters. (1) The return index (Datastream variable RI) is rounded off by Datastream to the nearest tenth, and this rounding introduces substantial errors in returns of low RI stocks. Therefore, if the return index of a stock is below 3 in a day, we set the corresponding return to a missing value for that day.[5] (2) If the return on a stock is greater than 300 percent in a day, we set that return to a missing value. (3) If the absolute value of changes in capitalization is more than 50 percent in one day, the return for this stock is set to a missing value on that day. (4) If the price of a stock falls by more than 90 percent in a day and it has increased by more than 200 percent within the previous 20 days (approximately a trading month), we set the returns between the two dates to missing values. (5) If the price of a stock increases by more than 100 percent in a day and has decreased by more than 200 percent within the previous 20 days, we set the returns between the two dates to missing values.

In a related study, Ang, Hodrick, Xing, and Zhang (2009) also investigate the cross-sectional IV effect using the Datastream data for the G7 countries. Their empirical approach

[5] The beginning RI for each stock is set at 100 by the DataStream. Thus, an RI of 3 or below indicates that the firm has lost 97% or more of its value over its life.

differs from ours in several ways. First, while these authors remove 5% of stocks with the smallest market capitalization, they do not consider the specific filters as used in this paper, which result in smaller sample reduction. Second, these authors use a shorter sample spanning the period January 1980 to December 2003. Third, these authors do not compare the Datastream data with the CRSP data for the U.S. Nevertheless, it is comforting to note that the main findings in the two studies are qualitatively similar.

IV. U.S. Evidence

We first discuss the empirical results for the modern sample over the period 1964 to 2005, which is similar to that used by Ang, Hodrick, Xing, and Zhang (2006). We then show that the results are qualitatively similar for the long sample over the period 1926 to 2005 and for the early sample over the period 1926 to 1963.

A. The Modern Sample: 1963 to 2005

Because small stocks have substantially higher IV than do large stocks (e.g., Pastor and Veronesi (2003)), we explicitly control for size when forming portfolios. We first sort stocks equally into 5 portfolios by market capitalization and then sort the stocks within each size quintile equally into 5 portfolios by the CAPM-based IV. Because Ghysels, Santa-Clara, and Valkanov (2005) show that realized variance is a function of long distributed lags of past daily stock returns, we use quarterly MV and VWAIV to forecast one-quarter-ahead stock returns. We convert monthly portfolio returns into quarterly returns by simple compounding.

We first confirm the finding by Ang, Hodrick, Xing, and Zhang (2006) that there is a significant cross-sectional IV effect in the updated modern sample. Panel A of Table 1 reports the average excess return for each of the 25 portfolios sorted by size and the CAPM-based IV.

S1 is the quintile of stocks with the smallest market capitalization and S5 is the quintile of stocks with the largest market capitalization. Within each size quintile, IV1 is the quintile of stocks with the lowest IV and IV5 is the quintile of stocks with the highest IV. Holding size constant, the quintile of stocks with the highest IV has lower average excess returns than do the other IV quintiles. Panel B reports the CAPM-based alpha for the return on a hedge portfolio that is long in IV1 and short in IV5. Alphas are significantly positive for the second to fifth size quintiles, and are positive and marginally significant for the first size quintile. Alphas are substantially larger than the differences in raw returns (as reported in panel A). This is because loadings on the market risk are smaller for low IV stocks than for high IV stocks.

Panel C of Table 1 shows that within each size quintile, the standard deviation of the CAPM-adjusted portfolio returns increases with IV. Because these portfolios are reasonably well diversified, the pattern suggests that portfolios with high IV stocks might be more sensitive to the risk factor(s) omitted from CAPM than are portfolios with low IV stocks.

In panels D to H of Table 1, we present the OLS (ordinary least squares) estimation results of forecasting one-quarter-ahead excess portfolio returns using MV and VWAIV. Panels D and F show that for all portfolios, the coefficients on MV are positive and statistically significant at least at the 10% level. Within each size quintile, the coefficients on MV increase monotonically from IV1, the quintile of stocks with the lowest IV, to IV5, the quintile of stocks with the highest IV. Panels E and G show that the coefficients on VWAIV are negative for all portfolios; they are also statistically significant at least at the 10% level in most cases. Within each size quintile, the coefficients on VWAIV decrease monotonically from IV1 to IV5, and the spread in loadings between IV1 and IV5 is quite substantial.

Panel H of Table 1 shows that within each size quintile, R^2—a measure of the portion of predictable variation in the portfolio returns—increases substantially from IV1 to IV5. For example, across the size quintiles, the average R^2 is about 1% for IV1, compared with about 10% for IV5. This pattern is consistent with the hypothesis that high IV stocks are more sensitive to discount-rate shocks than are low IV stocks. In subsection IV.C below, we show that returns on high IV stocks have significant predictive power for market returns, while the predictive power of low IV stocks is negligible.

Panel A of Table 2 investigates whether the coefficients on MV and VWAIV in the forecasting regression help explain the cross-section of stock returns on portfolios sorted by the CAPM-based IV. We use the Fama and MacBeth (1973) procedure in the cross-sectional regression. For each quarter, we run a regression of the 25 excess portfolio returns on the coefficients of MV and VWAIV obtained from the time-series regressions, as reported in panels D and E of Table 1, respectively. Row 1 of Table 2 reveals a strong link between time-series and cross-sectional stock return predictability. The risk premium on VWAIV is positive and statistically significant at the 1% level, according to the t-statistic calculated using the Shanken (1992) corrected standard error. Moreover, the risk premium on MV is also positive and statistically significant at the 5% level. Overall, MV and VWAIV jointly account for 63% of cross-sectional variation in average portfolio returns. The cross-sectional R^2 is moderate possibly because of the relatively short sample used in the regression. As we show in the next subsection, it increases substantially to over 80% for the long U.S. sample.

We also investigate whether IVF—the equal-weighted average of the return difference between IV1 and IV5 across all size quintiles is a proxy of systematic risk. In the cross-sectional regression, we also include the market (MKT) and size (SMB) factors obtained from Ken French at Dartmouth College. We include the size factor to control for the potential bias introduced by forming portfolios first by market capitalization. The size factor may also capture systematic risk that is not explained by MKT and IVF. Row 2 of Table 2 shows that the factor IVF is positively priced and the associated risk premium is statistically significant at the 5% level. Overall, the three factors jointly account for about 50% of cross-sectional variation in average portfolio returns. The moderate R^2 again reflects a power issue—it increases substantially to over 80% for the long U.S. sample, as we show in the next subsection.

If IVF is a proxy of systematic risk—e.g., a hedging factor in Merton's (1973) ICAPM—its variance, which we dub as V_IVF, forecasts stock returns when in conjunction with MV.[6] Consistent with this conjecture, we find a significantly negative relation between V_IVF and future market returns, while the relation is again positive for MV in the multivariate regression. Moreover, V_IVF is closely correlated with VWAIV, with a correlation coefficient of about 80%; and the two variables have qualitatively similar predictive power for market returns. For brevity, these results are not reported but are available on request. In Table 2, we investigate whether loadings on lagged V_IVF and on lagged MV help explain the cross-section of stock returns on the 25 portfolios sorted on size and the CAPM-based IV. Row 3 shows that both V_IVF and MV carry a positive risk premium, which is statistically significant at the 1% and 10% levels, respectively. Interestingly, after orthogonalizing V_IVF by VWAIV, we find that the residual, V_IVF^{+}, has negligible explanatory power for the cross-sectional of stock return (row 4). The close relation between V_IVF and VWAIV suggests that VWAIV forecasts stock returns possibly because it is a proxy of the variance of a hedging factor omitted from CAPM.

To summarize, consistent with the rational pricing explanation, we find a close relation between the time-series and cross-sectional IV effects over the modern period 1964 to 2005.

[6] V_IVF is the sum of squared daily IVF in a quarter.

B. The Full Sample: 1926 to 2005

As a robustness check, we also investigate the relation between the time-series and cross-sectional IV effects using the long U.S. sample over the period 1926 to 2005. Table 3 shows that the main results obtained from the long sample are qualitatively similar to those for the modern sample (as reported in Table 1). First, the CAPM-based alphas for the return difference between IV1 (quintile of stocks with the lowest IV) and IV5 (quintile of stocks with the highest IV) are always positive; moreover, they are statistically significant at the 10% level for smallest size quintile and at the 1% level for the other size quintiles (panel B). Second, the coefficients on MV are always positive and are substantially larger for high IV stocks than for low IV stocks (panel D). Lastly, the coefficients on VWAIV are always negative and are substantially smaller for high IV stocks than for low IV stocks (panel E). Note that we also find qualitatively similar results over the early period 1926 to 1963; for brevity, they are not reported but are available on request. The cross-sectional IV effect, therefore, is not specific to the modern U.S. sample.

Panel B of Table 2 reports the Fama and MacBeth cross-sectional regression results for the long U.S. sample, which are qualitatively similar to those for the modern U.S. sample (as reported in panel A of Table 2). Row 5 shows that loadings on both VWAIV and MV are positively and significantly priced, with the cross-sectional R^2 of about 81%. Similarly, the risk factor IVF is also positively and significantly priced in the cross-sectional regression; and the associated R^2 is about 81% (row 6). Moreover, loadings on V_IVF and MV are positively and significantly priced, with the cross-sectional R^2 of about 63% (row 7). Lastly, if orthogonalizing V_IVF by VWAIV, we find that the residual, V_IVF$^+$, carries a negative risk premium; by contrast, the risk premia of VWAIV and MV remain positive and highly significant (row 8). This result again reflects the close relation between V_IVF and VWAIV.

As indicated by t-statistics and the cross-sectional R^2, the explanatory power of the proposed risk factors is noticeably stronger for the long sample (panel B of Table 3) than for the modern sample (panel A of Table 3). The difference reflects mainly the fact that, if the data-generating process is relatively stable across time, we should improve the power of the tests by using a longer sample (as in panel B of Table 3). To illustrate this point, panel C of Table 3 reports the cross-sectional regression results using the early sample over the period 1926Q4 to 1963Q4. Row 9 shows that the results for the specification with VWAIV and MV as the explanatory variables are qualitatively similar to those reported in panels A and B. For example, the risk premia for VWAIV and MV are positive and statistically significant at the 5% and 10% levels, respectively; moreover, the two variables jointly account for about 77% of cross-sectional variation in average portfolio returns. For the cross-sectional regression that includes IVF (row 10) or V_IVF (row 11) as a risk factor, the results obtained from the early sample are similar to, but somewhat weaker than, those obtained from the modern or long samples. In the pre-1964 sample, while loadings on IVF and V_IVF are positively priced, the associated risk premia are statistically insignificant at the 10% level, however. One possible explanation is that the stock market is quite volatile in the early sample because of the 1929 stock market crash, the Great Depression, and the World War II. This fact may also explain why VWAIV and MV have relatively weaker forecasting power for portfolio returns in the long sample (as reported in Table 3) than in the modern sample (as reported in Table 1).

To summarize, we find qualitatively similar results using both the long and early U.S. samples. The results suggest that the time-series and cross-sectional IV effects might reflect systematic risk. In the next subsection, we provide some tentative tests of the hypothesis that IV is a proxy of loadings on discount-rate shocks.

C. Additional Robustness Tests

Many authors, e.g., Graham and Dodd (1934), Basu (1977, 1983), Ball (1978), and Rosenberg, Reid, and Lanstein (1985), have found that stocks with high B/M have higher expected returns than do stocks with low B/M. The return difference, which Fama and French (1996) dub as HML, remains significantly positive even after controlling for its loadings on the market risk. The B/M effect is one of the most prominent anomalies in the asset pricing literature, and a number of explanations have been proposed. Among them, Fama and French (1996) suggest that the B/M effect reflects intertemporal pricing, i.e., HML is a hedging risk factor of Merton's (1973) ICAPM.[7] Fama and French's conjecture is consistent with recent empirical studies by Brennan, Wang, and Xia (2004), Campbell and Vuolteenaho (2004), Petkova (2006), and Hahn and Lee (2006), who find that discount-rate shocks have significant explanatory power in explaining the B/M effect.[8] Therefore, if the IV effect also reflects intertemporal asset pricing, it may be closely related to the B/M effect in a systematic manner. This hypothesis is plausible also because there is a close relation between IV and B/M in the modern U.S. data, as documented by Pastor and Veronesi (2003) and others.

As conjectured, we find that HML is closely correlated with IVF over the modern period 1963Q1 to 2005Q4, with a correlation coefficient of about 50%.[9] More importantly, Table 4 shows that IVF performs just as well as HML in explaining the 25 Fama and French (1993)

[7] A partial list of the other possible explanations includes distress risk, e.g., Fama and French (1992); mispricing pricing, e.g., Lakonishok, Shleifer, and Vishny (1994); data snooping, e.g., MacKinlay (1995); and conditional CAPM, e.g., Lettau and Ludvigson (2001), Petkova and Zhang (2005), and Ang and Chen (2007). Recent authors, e.g., Berk, Green, and Naik (1999), Gomes, Kogan, and Zhang (2003), Zhang (2005), and Lettau and Wachter (2007), have developed partial equilibrium models to investigate the B/M effect theoretically.

[8] Our results are also potentially consistent with the theoretical work by Zhang (2005), who relates the B/M effects to time-varying equity premium in the conditional CAPM context.

[9] We obtain the monthly portfolio return data from Ken French at Dartmouth College and convert monthly returns to quarterly returns through simple compounding. We focus only on the modern sample because several recent studies, e.g., Campbell Vuolteenaho (2004), Petkova and Zhang (2005), Ang and Chen (2007), and Fama and French (2006), find that CAPM explains the B/M effect in the early period 1926 to 1963 but not in the modern sample. By contrast, the IV effect appears to be a more pervasive phenomenon than does the B//M effect because as we show in the next section, it cannot be explained by CAPM in the early sample.

portfolios sorted by size and B/M. Row 1 replicates the well-known empirical result that HML is significantly priced; and the Fama and French 3 factors account for about 79% of the cross-sectional variation in portfolio returns. When replacing HML by IVF, we find that IVF is also positively and significantly priced, with a cross-sectional R^2 of about 83% (row 2). To investigate further whether HML and IVF have similar explanatory power for the cross-sectional stock returns, we orthogonalize IVF by HML and find that the residual, IVF^+, is only marginally significant in the cross-sectional regression (row 3). Similarly, when orthogonalizing HML by IVF, we find that the residual, HML^+, has negligible explanatory power (row 4). Therefore, HML and IVF appear to have similar explanatory power for the cross-section of stock returns.

In panel B of Table 4, we investigate whether loadings on variances of risk factors explain the 25 Fama and French portfolios. Both MV and VWAIV are positively and significantly priced at the 5% and 1% levels, respectively (row 5). Similarly, the realized variance of HML, dubbed as V_HML, is positively and significantly priced at the 1% when in conjunction with MV (row 6); and MV is positively and significantly priced at the 5% level as well.[10] Interestingly, V_IVF is also positively and significantly priced at the 1% level when in conjunction with MV (row 7). V_HML, V_IVF, and VWAIV have similar cross-sectional explanatory power because the three variables are closely correlated with each other. For example, if orthogonalizing V_HML by VWAIV, we find that the residual, V_HML^+, has negligible explanatory power for the cross-section of stock returns (row 8). The result is qualitatively similar for the V_IVF (row 9). These results highlight a strong link between the time-series and cross-sectional IV effects.

As a robustness check, we test whether IVF helps explain the expected returns on momentum or industry portfolios and find that its explanatory power is rather weak. Given the

[10] Realized variance of HML is the sum of squared daily HML in a quarter.

strong correlation between IVF and HML, the result should not be too surprising because HML does not explain the cross-section of stock returns on momentum (Fama and French (1996)) and industry (Fama and French (1997) portfolios either. For brevity, these results are not reported here but are available on request.

Because discount rates are unobservable, we are unable to test the risk-based explanation directly. For example, Campbell and Vuolteenaho (2004) use estimated innovations in the variables that forecast market returns as a measure of discount-rate shocks. Chen and Zhao (2008), however, have questioned their approach because it is potentially sensitive to the choice of forecasting variables. We can address this criticism partially using the hypothesis that high IV stocks are more sensitive to discount-rate shocks than are low IV stocks. One direct implication of this hypothesis is that high returns on lagged high IV stocks predict low future returns on the market as a whole. This implication is also consistent with the empirical finding by Eleswarapu and Reinganum (2004), who find that high lagged returns on growth stocks predict low future stock market returns, while the predictive power is negligible for value stocks. We have argued that there is a close relation between the B/M effect and the IV effect. Therefore, to be comparable with the results reported by Eleswarapu and Reinganum, we follow their approach closely. Over the post-1950 period, we use the returns on high IV stocks in the previous twelve quarters to forecast excess market returns in the following four quarters. Table 5 shows that, as expected, the return on the portfolio of high IV stocks (IV5) is negatively related to future market returns, and such a relation is statistically significant at the 5% level except for the second size quintile. In contrast, the predictive power is statistically insignificant for returns on portfolios of low IV stocks (IV1) at the conventional significance level. By construction, IVF also has significant predictive power for market returns because of its correlation with returns on high IV stocks. This result suggests that IVF is priced in the cross-section of stock returns possibly because it is a proxy of discount-rate shocks.

Many early studies, e.g., Campbell (1987), Glosten, Jagannathan, and Runkle (1993), and Whitelaw (1994), document a *negative* relation between conditional stock market risk and return. Scruggs (1998) and Guo and Whitelaw (2006) point out that the perverse negative risk-return relation in the stock market reflects an omitted variable problem because the expected excess market return also depends on its covariance with the hedging risk factor. If IVF is a proxy of the hedging factor, it might help uncover the positive relation between conditional market return and variance. To address this issue, we estimate a monthly bivariate GARCH model using IVF as a proxy of the hedging risk factor and report the results in Table 6. We estimate the unrestricted model in row 1 and impose the restrictions of zero intercepts and the identical prices of risk across assets in row 2. Interestingly, for both specifications, we uncover a positive relation between conditional excess market return and variance after controlling for its conditional covariance with IVF. The hedging risk factor, IVF, is significantly priced as well.

To summarize, IVF is closely related to HML—an empirical risk factor that has been interpreted as a proxy of investment opportunities. Using IVF as a proxy of the hedging factor also helps uncover the positive risk-return relation. Moreover, returns on high IV stocks are negatively correlated with future market returns, while the predictive power is negligible for low IV stocks. These results are consistent with the hypothesis that the cross-sectional IV effect reflects systematic risk.

V. International Evidence

A. Returns on Quintile Portfolios Sorted by IV

As another out-of-sample test, in this subsection we investigate the cross-sectional IV effect using international data. Table 7 presents the results for the value-weighted quintile portfolios sorted by the CAPM-based IV over the period March 1973 to December 2003 for G7 countries obtained from the Datastream data. Again, quintile 1 consists of stocks with the lowest IV and quintile 5 consists of stocks with the highest IV. In the column under title "1-5" we report the return difference between quintile 1 and quintile 5. We also report alphas for the return difference relative to a measure of excess world market returns obtained from Ken French at Dartmouth College. We do not control for size in the portfolio formation because the other G7 countries have far fewer stocks than does the U.S. For comparison, we also report the results for the U.S. obtained from the CRSP data (panel H) over the same period, which are qualitatively similar to those obtained from the Datastream data (panel G). This evidence provides confidence in the use of the Datastream data with the filters discussed in Section III.

Table 7 shows that the CAPM-adjusted return difference between the low and high IV quintiles is positive in all the other G7 countries except for Italy. Moreover, the positive difference is statistically significant at the 5% level for Canada and Germany and at the 10% level for France. For the Japanese stock market, the annualized return difference is about 5%, which is economically important albeit statistically insignificant. To summarize, we find a qualitatively similar cross-sectional IV effect in most of the other G7 countries.

In Table 7, we also investigate an early U.S. sample spanning the period February 1926 to June 1962. The data provide another out-of-sample test for the cross-sectional IV effect. Panel I shows that the return difference between the first and fifth quintiles is positive; however, it is economically small (1% a year) and statistically insignificant at the conventional level.

Therefore, in contrast with the post-1962 evidence by Ang, Hodrick, Xing, and Zhang (2006), a simple trading strategy of buying low IV stocks and shorting high IV stocks does not work well in the early period. The return difference, however, becomes economically large (7% a year) and statistically significant at the 10% level after we control for its loadings on the market risk. The results highlight the importance of controlling for the market risk in detecting the cross-sectional IV effect because high IV stocks tend to have larger market betas that do low IV stocks.

To summarize, consistent with the evidence obtained from the modern U.S. sample, we find that high IV stocks tend to have lower CAPM-adjusted returns than do low IV stocks in most of the other G7 countries as well as in the early U.S. sample. Therefore, the cross-sectional IV effect is a pervasive phenomenon and cannot be simply attributed to data mining.

B. Cross-Country Correlation of the CAPM-Based IV Effect

Many early studies have found that international equity markets are influenced by common economic forces. For example, Harvey (1991) shows that U.S. financial variables outperform their local counterparts in the forecast of international stock market returns. If IV is a proxy of discount-rate shocks, we expect that the cross-sectional IV effect should have strong comovement between the U.S. and the other G7 countries. Table 8 presents the cross-country correlation of the return difference between the first and fifth IV quintiles (as reported in Table 7). Except for Germany, the trading profits of the other G7 countries are indeed closely correlated with their U.S. counterpart, with the correlation coefficients ranging from 28% to 40%. The comovement among the other G7 countries, however, is relatively weak. The strong comovement of the cross-sectional IV effect between the other G7 countries and the U.S. is consistent with the results by Guo and Savickas (2008), who find that VWAIV and MV in the other G7 countries move closely to their U.S. counterparts. Moreover, U.S. VWAIV and MV jointly have significant predictive power for international stock market returns; and they even subsume the information content of their local counterparts in the forecasting regressions. To summarize, the U.S. stock market has a pervasive influence on international stock markets.

C. Relation between Time-Series and Cross-Sectional IV Effects in G7 Counties

In this subsection, we investigate the relation between time-series and cross-sectional IV effects in G7 countries. Portfolio returns are originally denominated in local currencies. For comparison, we convert them into returns in term of the U.S. dollar by applying the corresponding foreign exchange rates. The quarterly excess portfolio return is the difference between the portfolio return denoted in the U.S. dollar and the U.S. risk-free rate.

Table 9 presents the OLS estimation results of forecasting excess portfolio returns using U.S. MV and VWAIV. We use the U.S. variables as proxies for systematic risks of the world market because they subsume the information content of their local counterparts in the forecast of international stock market returns (see, e.g., Guo and Savickas (2008)).[11] We confirm that U.S. VWAIV and MV have significant predictive power for international portfolio returns. The results for the G7 countries are qualitatively similar to their U.S. counterparts, as reported in Tables 1 and 3. The coefficients are positive for MV and negative for VWAIV; they are statistically significant at least at the 10% level for most of the international portfolios. The coefficient on MV increases from low IV stocks to high IV stocks; by contrast, the coefficient on VWAIV decreases from low IV stocks to high IV stocks. As a result, the return on the hedging portfolio of buying low IV stocks and shorting high IV stocks correlates negatively with MV but positively with VWAIV. Also, R^2 increases from low IV stocks to high IV stocks. The results

[11] Using data of 37 international stock markets, Bali and Cakici (2009) find little support that world market risk is priced, indicating that international stock markets are not fully integrated. Our results differ from theirs because we focus on G7 countries, which arguably have a higher level of economic integration than does a broader set of countries studied in Bail and Cakici.

suggest that, consistent with the U.S. evidence, the cross-sectional IV effect in the international markets may also reflect systematic risk, which we investigate formally next.

Panel D of Table 2 presents the Fama and MacBeth (1973) cross-sectional regression results using 35 international portfolios sorted by IV, with 5 portfolios for each of the G7 countries. Consistent with the results obtained from U.S. data, row 13 shows that the risk premium associated with VWAIV is positive and statistically significant, with a cross-sectional R^2 of about 77%.[12] The risk premium associated with MV is also positive, although it is statistically insignificant according to the Shanken-corrected standard error. In row 14, we use the mimicking factor, IVF, along with the market and size factors to explain the cross-section of stock returns. For comparison with the results obtained using MV and VWAIV, we also use the U.S. factors. IVF is positively and significantly priced, and the associated cross-sectional R^2 is over 70%. We also use loadings on lagged U.S. V_IVF and lagged MV to explain the cross-section of returns. Row 15 shows that both factors are positively priced, and the associated risk premia are statistically significant at the 5% level for V_IVF and at the 10% level for MV. V_IVF and VWAIV have similar explanatory power. If we orthogonalize V_IVF by VWAIV, the residual, V_IVF^+, becomes statistically insignificant in the cross-section regression (row 16).

To summarize, the international data also provide additional support for the hypothesis that the IV effects reflect systematic risk.

[12] The loadings on MV and VWAIV are likely to be less precisely estimated for international stock returns than for U.S. stock returns for two reasons. First, the sample period is substantially shorter for international data than for the modern U.S. data. Second, international stock returns are more volatile than U.S. stock returns. To obtain precise estimates of the factor loadings, we restrict the intercept to be zero in the first-pass regression in row 13 of Table 2. The results reported in row 14 of Table 3 are not sensitive to such a restriction, however. This is because R^2 is much higher and factor loadings are much more precisely estimated in the regressions of portfolio returns on contemporaneous risk factors constructed using portfolio returns than in the forecasting regressions of portfolio returns on lagged variances.

VI. Model Diagnostics

This section conducts some diagnostic tests of IVF as a priced risk factor using the stochastic discount factor representation. For brevity, we only briefly discuss the main framework, which follows closely Cochrane (2001). The law of one price implies the existence of a stochastic discount factor, m_{t+1}, such that

(1) $$E_t(m_{t+1}R_{j,t+1}) = 0,$$

where $R_{j,t+1}$ is the excess return on the portfolio *j* at time *t*+1. We assume that the stochastic discount factor is approximately a linear function of the proposed risk factors, F_{t+1}:

(2) $$y_{t+1} = b_0 + b'F_{t+1},$$

where the coefficients b' are prices of risk. The linear stochastic discount factor model has an equivalent beta pricing model representation:

(3) $$E(R_j) = \beta_j'\Lambda,$$

where β_j' is a vector of the loadings of the portfolio *j* on the risk factors, $\Lambda = -R^0 \operatorname{cov}(F, F')b$ is a vector of risk premia, and R^0 is the risk-free rate or the return on a zero-beta asset.

We estimate the asset pricing equation (1) using Hansen's (1982) general method of moments (GMM). For robustness, we consider 3 commonly used weighing matrices: The identity weighting matrix; the inverted covariance matrix of the portfolio returns, as advocated by Hansen and Jagannathan (1997); and the optimal weighting matrix proposed by Hansen (1982). For the first two weighting matrices, we test the model's goodness of fit 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.

In Table 10, we use 10 U.S. portfolios of stocks with either the highest or the lowest IV within each size quintile, which are selected from the 25 portfolios sorted by size and IV, as used in Table 3. As in Lettau and Ludvigson (2001), we use only a subset of the portfolios because we want to mitigate the potential small sample bias of the GMM estimator. The model with MKT, SMB, and IVF as the risk factors is not rejected at the 1% level regardless of the weighting matrix used. 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 reasonably well in explaining the cross-section of stock returns. Moreover, the risk premium for IVF is always positive and statistically significant.

To investigate further the explanatory power of IVF for the portfolios sorted by size and IV, we report alphas in Table 11. Panel A reports the alpha based on the multifactor model with the excess market return (MKT), the size factor (SIZE), and IVF, while panel C reports the alpha based on CAPM. The absolute value of the alpha is usually smaller for the multifactor model than for CAPM. More importantly, panel B shows that the alpha based on the multifactor model is statistically significant at the 5% level for only 2 portfolios, compared with 14 portfolios for the CAPM-based alpha. The multifactor model thus performs noticeably better than CAPM.

Lastly, in Table 12, we use 14 portfolios constructed using international data, which are the quintile of stocks with the highest IV and the quintile of stocks with the lowest IV for each of the G7 countries. Again, we find that IVF is always significantly priced and the model is not rejected at the conventional significance level.

VI. Conclusion

Recent empirical studies find that IV has negative effects on expected stock returns in both the time-series and cross-sectional regressions. In this paper, we document a close link between the time-series and cross-sectional IV effects, suggesting that IV might be a proxy of risk. The return difference between low and high IV stocks, IVF, is significantly priced in the cross-section of stock returns. Loadings on lagged market variance and lagged average IV account for a significant portion of variation in average returns on portfolios sorted by IV. The variance of IVF is closely correlated with average IV, and the two variables have similar explanatory for the time-series and cross-sectional stock returns.

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Table 1 Portfolios Sorted by Size and IV: Modern Sample

	S1(smallest)	S2	S3	S4	S5(largest)
Panel A Sample Average Excess Returns					
IV1(lowest)	0.031	0.031	0.030	0.024	0.014
IV2	0.043	0.039	0.034	0.031	0.017
IV3	0.048	0.031	0.033	0.030	0.016
IV4	0.045	0.021	0.023	0.024	0.016
IV5(highest)	0.027	-0.013	-0.013	-0.002	0.010
Panel B Alpha Based on CAPM					
1-5	0.019	0.057	0.055	0.039	0.015
	(1.751)	(6.918)	(7.460)	(5.582)	(2.545)
Panel C Standard Deviation of CAPM-Corrected Residuals of Portfolio Returns					
IV1(lowest)	0.086	0.066	0.056	0.046	0.027
IV2	0.109	0.079	0.062	0.050	0.024
IV3	0.131	0.084	0.070	0.050	0.022
IV4	0.153	0.105	0.082	0.055	0.027
IV5(highest)	0.185	0.133	0.102	0.079	0.055
Panel D Parameter Estimates MV					
IV1(lowest)	6.290	6.060	5.734	4.907	4.546
IV2	13.872	11.513	9.462	7.671	7.789
IV3	18.593	15.038	13.017	10.022	10.337
IV4	21.267	19.744	16.496	14.235	12.933
IV5(highest)	25.343	19.821	18.368	18.212	17.642
Panel E Parameter Estimates VWAIV					
IV1(lowest)	-1.226	-0.985	-0.698	-0.646	-1.256
IV2	-2.781	-2.204	-1.731	-1.424	-2.102
IV3	-3.526	-3.157	-2.562	-2.288	-2.791
IV4	-4.811	-4.765	-3.985	-3.888	-4.200
IV5(highest)	-6.436	-5.673	-5.011	-5.487	-5.913
Panel F T-Statistics MV					
IV1(lowest)	1.981	2.293	2.121	1.765	2.277
IV2	2.891	2.897	2.666	2.203	3.120
IV3	3.104	3.136	2.848	2.537	3.242
IV4	2.894	3.082	3.046	3.264	4.216
IV5(highest)	2.912	2.925	3.021	3.238	4.142
Panel G T-Statistics VWAIV					
IV1(lowest)	-1.588	-1.638	-1.030	-1.008	-2.204
IV2	-2.012	-2.323	-1.975	-1.714	-3.485
IV3	-1.795	-2.453	-2.031	-2.279	-3.912
IV4	-2.135	-2.840	-2.426	-3.017	-4.325
IV5(highest)	-2.539	-2.921	-2.780	-2.769	-4.172
Panel H R^2					
IV1(lowest)	0.000	0.014	0.027	0.018	0.028
IV2	0.046	0.050	0.048	0.029	0.066
IV3	0.076	0.068	0.066	0.052	0.099
IV4	0.067	0.091	0.083	0.085	0.137
IV5(highest)	0.066	0.067	0.077	0.108	0.187

Note: We first sort all CRSP common stocks equally into 5 portfolios by market capitalization and then sort the stocks within each size quintile equally into 5 portfolios by the CAPM-based IV. S1 is the quintile portfolio of stocks with the smallest market capitalization and S5 is the quintile portfolio of stocks with the largest market capitalization. Within each size quintile, IV1 is the quintile portfolio of stocks with the lowest IV and IV5 is the quintile portfolio of stocks with the highest IV. We construct the portfolio returns using the value weighting scheme. The excess portfolio return is the difference between the portfolio return and the risk-free rate. We regress the one-quarter-ahead excess portfolio return on MV and VWAIV and report the OLS estimation results in panels D to H. The sample spans the period 1964Q1 to 2005Q4. T-statistics are reported in parentheses in panel B. We calculate t-statistics using the heteroskedasticity-consistent standard error.

Table 2 Fama and MacBeth Regressions for Portfolios Sorted by IV

	Constant	MKT	SMB	IVF	VWAIV	MV	V_IVF	V_IVF$^+$	R^2
Panel A Modern U.S. Sample: 1964Q1 to 2005Q4									
1	0.019				0.020	0.005			0.628
	(1.751)				(3.163)	(2.054)			
2	0.031	-0.018	0.012	0.022					0.480
	(3.088)	(-1.524)	(2.546)	(2.419)					
3	0.014					0.005	0.010		0.448
	(1.288)					(1.780)	(2.980)		
4	0.016				0.025	0.007		-0.002	0.591
	(1.234)				(4.556)	(3.130)		(-0.911)	
Panel B Full U.S. Sample: 1926Q4 to 2005Q4									
5	0.030				0.021	0.008			0.813
	(3.631)				(5.565)	(2.769)			
6	0.003	0.015	0.015	0.024					0.807
	(0.363)	(1.519)	(3.124)	(3.675)					
7	0.023					0.005	0.015		0.628
	(3.002)					(1.767)	(5.440)		
8	0.020				0.020	0.009		-0.008	0.893
	(3.266)				(5.376)	(3.224)		(-3.233)	
Panel C Early U.S. Sample: 1926Q4 to 1963Q4									
9	0.026				0.010	0.007			0.768
	(2.352)				(2.265)	(1.830)			
10	0.024	0.004	0.015	0.008					0.765
	(2.356)	(0.261)	(2.195)	(0.948)					
11	0.025					0.007	0.006		0.772
	(2.096)					(1.586)	(1.235)		
12	0.032				0.012	0.010		-0.006	0.804
	(2.490)				(3.451)	(3.775)		(-2.538)	
Panel D International Sample: 1973Q2 to 2003Q4									
13	0.014				0.022	0.006			0.773
	(0.801)				(2.125)	(1.381)			
14	0.006	0.019	-0.018	0.037					0.721
	(0.351)	(0.987)	(-1.090)	(2.128)					
15	0.013					0.006	0.0075		0.353
	(1.034)					(1.777)	(2.133)		
16	0.011				0.022	0.006		-0.000	0.833
	(0.691)				(1.774)	(1.211)		(-0.209)	

Note: In panel A to C, we sort all CRSP common stocks equally into 5 portfolios by market capitalization and then sort the stocks within each size quintile equally into 5 portfolios by the CAPM-based IV. In panel D, we use 35 international portfolios sorted by the CAPM-based IV, with 5 portfolios for each of the G7 countries. MV is realized stock market variance; VWAIV is value-weighted average idiosyncratic variance; MKT is the excess stock market return; and SMB is the size factor of the Fama and French (1996) 3-factor model. IVF is the equal-weighted average of the return difference between IV1 (quintile with lowest IV) and IV5 (quintile with the highest IV) across all size quintiles; and V_IVF is realized variance of IVF. V_IVF$^+$ is the residual of the regression of V_IVF on a constant and VWAIV. The Shanken (1992) corrected t-statistics are reported in parentheses.

Table 3 Portfolios Sorted by Size and IV: Full Sample

	S1(smallest)	S2	S3	S4	S5(largest)
	Panel A Sample Average Excess Returns				
IV1(lowest)	0.046	0.039	0.035	0.028	0.020
IV2	0.056	0.045	0.037	0.031	0.022
IV3	0.057	0.043	0.039	0.033	0.022
IV4	0.051	0.032	0.029	0.032	0.021
IV5(highest)	0.050	0.004	0.006	0.014	0.016
	Panel B Alpha Based on CAPM				
1-5	0.016	0.049	0.044	0.031	0.017
	(1.746)	(9.013)	(9.069)	(6.293)	(4.117)
	Panel C Standard Deviation of CAPM-Corrected Residuals of Portfolio Returns				
IV1(lowest)	0.108	0.069	0.052	0.040	0.026
IV2	0.148	0.084	0.063	0.046	0.025
IV3	0.164	0.117	0.068	0.051	0.024
IV4	0.205	0.116	0.079	0.063	0.030
IV5(highest)	0.238	0.121	0.092	0.077	0.050
	Panel D Parameter Estimates MV				
IV1(lowest)	6.131	3.778	2.447	1.169	1.417
IV2	9.103	5.205	3.393	2.274	1.833
IV3	9.275	7.083	4.548	2.862	2.396
IV4	9.763	8.119	4.850	5.823	4.040
IV5(highest)	11.507	6.707	6.879	6.722	5.058
	Panel E Parameter Estimates VWAIV				
IV1(lowest)	-2.259	-1.352	-0.681	-0.469	-0.906
IV2	-2.654	-1.531	-1.001	-0.687	-1.129
IV3	-2.509	-1.457	-1.461	-0.865	-1.329
IV4	-2.818	-2.912	-2.304	-2.249	-2.140
IV5(highest)	-3.732	-3.351	-3.299	-3.350	-3.064
	Panel F T-Statistics MV				
IV1(lowest)	1.498	1.260	0.999	0.616	0.850
IV2	1.511	1.321	1.016	0.909	1.015
IV3	1.449	1.278	1.241	0.905	1.069
IV4	1.329	1.551	1.281	1.495	1.562
IV5(highest)	1.474	1.546	1.690	1.636	1.673
	Panel G T-Statistics VWAIV				
IV1(lowest)	-1.841	-1.456	-0.875	-0.776	-1.689
IV2	-1.490	-1.327	-1.008	-0.911	-2.057
IV3	-1.270	-0.990	-1.210	-0.927	-2.174
IV4	-1.356	-1.907	-1.790	-1.857	-2.715
IV5(highest)	-1.723	-2.402	-2.425	-2.359	-2.750
	Panel H R^2				
IV1(lowest)	0.043	0.025	0.022	0.001	0.005
IV2	0.053	0.032	0.014	0.011	0.006
IV3	0.044	0.043	0.024	0.008	0.012
IV4	0.035	0.045	0.022	0.029	0.025
IV5(highest)	0.036	0.023	0.032	0.035	0.038

Note: We first sort all CRSP common stocks equally into 5 portfolios by market capitalization and then sort the stocks within each size quintile equally into 5 portfolios by the CAPM-based IV. S1 is the quintile portfolio of stocks with the smallest market capitalization and S5 is the quintile portfolio of stocks with the largest market capitalization. Within each size quintile, IV1 is the quintile portfolio of stocks with the lowest IV and IV5 is the quintile portfolio of stocks with the highest IV. We construct the portfolio returns using the value weighting scheme. The excess portfolio return is the difference between the portfolio return and the risk-free rate. We regress the one-quarter-ahead excess portfolio return on MV and VWAIV and report the OLS estimation results in panels D to H. The sample spans the period 1926Q4 to 2005Q4. T-statistics are reported in parentheses in panel B. We calculate t-statistics using the heteroskedasticity-consistent standard error.

Table 4 Explaining the 25 Fama and French Portfolios Sorted by Size and B/M

				Panel A Levels of Risk Factors				
	Constant	MKT	HML	SMB	IVF	HML^+	IVF^+	R^2
1	0.031	-0.016	0.014	0.008				0.791
	(2.392)	(-1.070)	(3.011)	(1.717)				
2	0.038	-0.022		0.009	0.023			0.826
	(2.893)	(-1.562)		(2.068)	(1.985)			
3	0.028	-0.013	0.013	0.009			0.016	0.831
	(2.043)	(-0.860)	(2.817)	(2.059)			(1.874)	
4	0.028	-0.013		0.009	0.018	0.004		0.831
	(2.043)	(-0.860)		(2.059)	(1.661)	(0.698)		
				Panel B Variances of Risk Factors				
	Constant	MV	VWAIV	V_HML	V_IVF	V_HML(+)	V_IVF(+)	
5	0.019	0.005	0.020					0.628
	(1.752)	(2.054)	(3.163)					
6	0.014	0.006		0.003				0.582
	(1.190)	(2.148)		(3.419)				
7	0.014	0.005			0.010			0.448
	(1.288)	(1.780)			(2.980)			
8	0.015	0.006	0.023			0.000		0.647
	(1.457)	(2.970)	(5.050)			(0.575)		
9	0.015	0.007	0.025				-0.001	0.612
	(1.285)	(3.217)	(4.811)				(-0.690)	

Note: We report the Fama and MacBeth (1973) cross-sectional regression results using excess returns on the 25 Fama and French (1996) portfolios sorted by size and B/M. The excess portfolio return is the difference between the portfolio return and the risk-free rate. MKT, HML, and SMB are the excess stock market return, the value premium, and the size premium, respectively, of the Fama and French (1996) 3-factor model. IVF is the equal-weighted average of the return difference between IV1 (quintile with lowest IV) and IV5 (quintile with the highest IV) across all size quintiles. HML^+ is the residual from the regression of HML on a constant and IVF. IVF^+ is the residual from the regression of IVF on a constant and HML. MV is realized market variance; VWAIV is average idiosyncratic variance; V_HML is realized variance of HML; and V_IVF is realized variance of IVF. V_HML^+ is the residual from the regression of V_HML on a constant and VWAIV. V_IVF^+ is the residual from the regression of V_IVF on a constant and VWAIV. The sample spans the period 1964Q1 to 2005Q4. We repot the Shanken (1992) corrected t-statistic in parentheses.

Table 5 Forecasting Stock Market Returns Using Lagged Portfolio Returns

		IV1 (lowest)	RSQ	IV5 (highest)	R^2
1	S1 (smallest)	-0.139	0.012	-0.224	0.076
		(0.315)		(0.023)	
2	S2	-0.175	0.012	-0.152	0.030
		(0.300)		(0.149)	
3	S3	-0.163	0.007	-0.270	0.061
		(0.337)		(0.043)	
4	S4	-0.103	0.003	-0.305	0.062
		(0.446)		(0.034)	
5	S5 (largest)	-0.185	0.009	-0.376	0.070
		(0.370)		(0.033)	

Note: We sort CRSP common stocks equally into 5 portfolios by size, and then within each size portfolio we sort the stocks equally into 5 portfolios by the CAPM-based IV. The portfolio returns are calculated using the value weight. IV1 is the portfolio of stocks with the highest IV and IV5 is the portfolio of stocks with the lowest IV. 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. We report the bootstrapped p-values in parentheses.

Table 6 Estimating ICAPM Using Bivariate Asymmetric BEKK Models

	MKT Equation			IVF Equation			LL
	α_M	$\gamma_{M,M}$	$\gamma_{M,I}$	α_I	$\gamma_{I,M}$	$\gamma_{I,I}$	
1	0.004	4.298	3.870	0.010	7.456	2.681	3478.510
	(1.596)	(2.259)	(2.142)	(6.016)	(2.259)	(1.947)	
2		5.902	4.543		5.902	4.543	3430.790
		(3.769)	(4.013)		(3.769)	(4.013)	

Note: The table reports the estimation results of ICAPM using the asymmetric BEKK model proposed by Engle and Kroner (1995):

$$R_{t+1} = \alpha_M + \gamma_{M,M}\sigma^2_{M,t} + \gamma_{M,I}\sigma_{M,I,t} + \upsilon_{M,t+1}$$
$$IVF_{t+1} = \alpha_I + \gamma_{I,M}\sigma_{M,I,t} + \gamma_{I,I}\sigma^2_{I,t} + \upsilon_{I,t+1},$$

where R_{t+1} is the excess stock market return and IVF_{t+1} is the return on a hedge portfolio that is long in low IV stocks and short in high IV stocks. We estimate the BEKK model using the quasi-maximum likelihood method. Row 1 is the unrestricted ICAPM. In row 2, we impose the ICAPM restrictions on the parameters: $\alpha_M = \alpha_I = 0$, $\gamma_{M,M} = \gamma_{I,M}$, and $\gamma_{M,I} = \gamma_{I,I}$. The sample spans the period February 1926 to December 2005. T-statistics are reported in parentheses.

Table 7 Return on Quintile Portfolios Sorted by IV in G7 Countries

1(lowest)	2	3	4	5(highest)	1-5	T-stat	Alpha	T-stat
Panel A Canada								
0.010	0.010	0.006	0.001	-0.003	0.013	2.309	0.014	2.572
Panel B France								
0.015	0.013	0.013	0.008	0.009	0.006	1.394	0.008	1.857
Panel C Germany								
0.011	0.008	0.006	0.009	0.004	0.006	2.526	0.006	2.422
Panel D Italy								
0.013	0.012	0.012	0.012	0.014	-0.001	-0.275	-0.000	-0.122
Panel E Japan								
0.005	0.007	0.007	0.006	0.002	0.004	1.230	0.004	1.436
Panel F U.K.								
0.015	0.013	0.013	0.014	0.014	0.001	0.244	0.002	0.717
Panel G U.S.								
0.010	0.011	0.012	0.010	0.003	0.007	1.576	0.009	2.252
Panel H U.S (CRSP)								
0.011	0.011	0.011	0.008	0.000	0.011	2.593	0.013	3.347
Panel I U.S. (CRSP, February 1926 to June 1962)								
0.010	0.010	0.011	0.010	0.008	0.001	0.379	0.006	1.923

Note: The table reports monthly returns on quintile portfolios equally sorted by the CAPM-based IV. Unless otherwise indicated, we use Datastream data over the period March 1973 to December 2003. The first quintile includes stocks with the lowest IV and the fifth quintile includes stocks with the highest IV. Column under title "1-5" reports the return difference between the first and fifth IV quintiles. Column "Alpha" reports the alpha of the return difference between the first and fifth IV quintiles relative to a measure of the world excess market return. We calculate the t-statistics using the heteroskedasticity-consistent standard error.

Table 8 Cross-Country Correlation of the IV Effect

	Canada	France	Germany	Italy	Japan	U.K.	U.S.	U.S. (CRSP)
Canada	1.00							
France	0.31	1.00						
Germany	0.17	0.01	1.00					
Italy	0.06	0.26	-0.03	1.00				
Japan	0.07	0.11	-0.05	0.18	1.00			
U.K.	0.16	0.32	0.01	0.26	0.15	1.00		
U.S.	0.28	0.41	-0.03	0.28	0.30	0.40	1.00	
U.S. (CRSP)	0.28	0.42	-0.01	0.28	0.28	0.44	0.94	1.00

Note: The table reports the correlation coefficients of the return difference between the quintile of stocks with the lowest CAPM-based IV (IV1 in Table 7) and the quintile of stocks with the highest IV (IV5 in Table 7) across the G7 countries. Unless otherwise indicated, we use the Datastream data. The monthly data span the period March 1973 to December 2003.

Table 9 Loadings on Market Variance and Average Idiosyncratic Variance: G7 Countries

	Const	T-stat	MV	T-stat	VWAIV	T-stat	R^2
			Panel A Canada				
1(lowest)	0.001	0.068	5.708	2.661	-0.929	-1.271	0.013
2	0.014	0.908	8.017	2.843	-2.129	-2.017	0.028
3	0.036	1.743	11.881	2.862	-4.772	-3.447	0.100
4	0.002	0.115	16.289	4.099	-5.271	-4.392	0.098
5(highest)	-0.039	-1.228	30.601	1.839	-7.248	-2.260	0.153
1-5	0.039	1.294	-25.027	-1.443	6.424	2.001	0.111
			Panel B France				
1(lowest)	0.050	2.829	7.455	1.764	-2.921	-3.127	0.026
2	0.042	2.272	6.695	1.405	-2.558	-2.504	0.006
3	0.033	1.639	11.653	2.203	-3.546	-2.869	0.043
4	0.054	2.645	14.355	2.622	-5.799	-4.651	0.111
5(highest)	0.016	0.714	21.155	3.055	-5.764	-4.032	0.107
1-5	0.034	1.964	-13.045	-2.549	2.661	2.043	0.065
			Panel C Germany				
1(lowest)	0.034	2.216	5.775	1.695	-2.009	-2.369	0.008
2	0.037	2.225	2.506	0.838	-1.572	-1.634	-0.005
3	0.030	1.778	3.538	0.752	-1.932	-1.598	0.010
4	0.034	1.884	5.488	1.081	-2.180	-1.977	0.005
5(highest)	0.010	0.599	5.347	1.043	-1.668	-1.529	0.001
1-5	0.025	1.879	0.616	0.175	-0.442	-0.491	-0.020
			Panel D Italy				
1(lowest)	0.036	1.676	6.068	1.641	-2.447	-2.591	0.024
2	0.042	1.792	7.520	1.871	-3.195	-3.376	0.032
3	0.040	1.554	4.711	1.078	-2.503	-2.361	-0.004
4	0.043	1.756	7.022	1.737	-3.108	-3.255	0.013
5(highest)	0.047	1.805	9.970	1.935	-3.834	-2.945	0.027
1-5	-0.012	-0.643	-3.556	-1.154	1.299	1.267	-0.021
			Panel E Japan				
1(lowest)	0.026	1.452	0.931	0.316	-0.852	-1.023	-0.005
2	0.040	2.153	4.135	1.303	-2.175	-2.498	0.007
3	0.038	2.013	3.215	0.903	-1.944	-1.935	0.013
4	0.030	1.503	8.093	2.020	-2.941	-2.666	0.034
5(highest)	0.021	0.928	9.426	1.734	-3.397	-2.471	0.024
1-5	0.005	0.356	-8.560	-2.500	2.595	2.823	0.132
			Panel F U.K.				
1(lowest)	0.035	2.225	5.067	0.954	-1.663	-1.758	-0.002
2	0.020	1.221	7.461	1.068	-1.818	-1.457	-0.004
3	0.037	2.189	7.580	1.094	-2.633	-2.206	0.014
4	0.047	2.732	10.163	1.332	-3.827	-2.808	0.051
5(highest)	0.058	2.605	12.750	1.575	-4.843	-2.973	0.056
1-5	-0.023	-1.527	-7.609	-1.834	3.167	2.902	0.043
			Panel G U.S.				
1(lowest)	0.021	1.959	4.307	2.200	-1.281	-2.339	0.021
2	0.020	1.656	7.899	2.679	-2.228	-3.205	0.052
3	0.028	1.869	11.054	3.284	-3.388	-3.758	0.095
4	0.024	1.278	16.713	3.614	-5.089	-3.621	0.144
5(highest)	-0.005	-0.207	23.198	3.589	-6.559	-3.451	0.166
1-5	0.026	1.302	-18.891	-3.683	5.277	3.232	0.170

Note: The table reports the OLS estimation results of regressing excess portfolio returns on U.S. realized stock market variance (MV) and U.S. CAPM-based value-weighted average realized idiosyncratic variance (VWAIV). All returns are denoted in the U.S. dollar. For each country, we sort all stocks equally into 5 portfolios by the CAPM-based IV. The first quintile includes stocks with the lowest CAPM-based IV and the fifth quintile includes stocks with the highest CAPM-based IV. The quarterly data span the period 1973Q3 to 2003Q4. We calculate t-statistics using the heteroskedasticity-consistent standard error.

Table 10 Diagnostic Tests Using U.S. IV Portfolios: 1927Q1 to 2005Q4

	Prices of Risk (b)			Risk premium (Λ)			J-test	HJ-Dist
	MKT	SMB	IVF	MKT	SMB	IVF		
Panel A Identity Weighting Matrix								
1	2.125	8.487	6.643	0.020	0.021	0.033		0.105
	(2.356)	(2.743)	(6.430)	(1.550)	(1.622)	(2.439)		(0.023)
Panel B HJ Weighting Matrix								
2	3.378	5.075	6.373	0.026	0.010	0.036		20.069
	(4.691)	(2.888)	(6.504)	(2.259)	(1.352)	(3.178)		(0.021)
Panel C Optimal Weighting Matrix								
3	3.432	3.222	6.323	0.017	0.007	0.045	17.245	
	(5.354)	(2.241)	(6.747)	(1.891)	(0.131)	(4.509)	(0.016)	

Note: We estimate the stochastic discount factor models using ten portfolios of stocks with either highest or lowest IV selected from the 25 portfolios sorted by size and IV, as discussed in Table 3. The law of one price implies the existence of a stochastic discount factor, m_{t+1}, such that

$$E_t(m_{t+1}R_{j,t+1}) = 0 ,$$

where $R_{j,t+1}$ is the excess return on the portfolio j at time t+1. We assume that the stochastic discount factor is approximately a linear function of the proposed risk factors, F_{t+1}:

$$y_{t+1} = b_0 + b'F_{t+1} ,$$

where the coefficients b' are prices of risk. The linear stochastic discount factor model has an equivalent beta pricing model representation:

$$E(R_j) = \beta_j'\Lambda ,$$

where β_j' is a vector of the loadings of the portfolio j on the risk factors, $\Lambda = -R^0 \operatorname{cov}(F, F')b$ is a vector of the risk premia; and R^0 is the risk-free rate or the return on a zero-beta asset. We estimate the model using Hansen's (1982) general method of moments (GMM). For robustness, we consider 3 commonly used weighing matrices: The identity weighting matrix; the inverted covariance matrix of the portfolio returns, as advocated by Hansen and Jagannathan (1997); and the optimal weighting matrix proposed by Hansen (1982). For the first two weighting matrices, we test the model's goodness of fit 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. MKT is the excess market return; SMB is the size factor in the Fama and French (1993) 3-factor model; and IVF is the return difference between low and high IV stocks. All factors are constructed using U.S. data.

Table 11 Alpha of 25 Portfolios Sorted by Size and IV

	S1(smallest)	S2	S3	S4	S5(largest)
Panel A Alpha based on Multifactor Model of MKT, SIZE, and IVF					
IV1(lowest)	0.006	0.003	0.004	0.000	0.000
IV2	0.011	0.008	0.003	0.000	0.001
IV3	0.018	0.000	0.005	0.002	0.001
IV4	0.014	-0.003	0.003	0.000	0.002
IV5(highest)	0.028	-0.010	-0.011	-0.008	-0.002
Panel B T-Statistics of Alpha Based on Multifactor Model of MKT, SIZE, and IVF					
IV1(lowest)	0.983	1.115	1.607	0.025	-0.195
IV2	1.177	1.768	0.815	0.213	0.325
IV3	1.787	-0.054	1.634	0.905	0.388
IV4	1.049	-0.434	1.064	0.147	1.111
IV5(highest)	1.814	-2.400	-3.211	-1.898	-0.434
Panel C Alpha Based on CAPM					
IV1(lowest)	0.016	0.015	0.014	0.010	0.004
IV2	0.015	0.014	0.009	0.009	0.004
IV3	0.014	0.003	0.007	0.005	0.001
IV4	0.005	-0.007	-0.003	-0.002	-0.003
IV5(highest)	0.000	-0.033	-0.029	-0.021	-0.013
Panel D T-Statistics of Alpha Based on CAPM					
IV1(lowest)	2.965	4.204	5.088	4.346	2.734
IV2	1.999	3.166	2.779	3.612	2.485
IV3	1.651	0.533	1.943	1.664	0.606
IV4	0.542	-1.270	-0.781	-0.645	-1.884
IV5(highest)	0.023	-5.088	-5.749	-5.009	-4.246

Note: We first sort all CRSP common stocks equally into 5 portfolios by market capitalization and then sort the stocks within each size quintile equally into 5 portfolios by the CAPM-based IV. S1 is the quintile portfolio of stocks with the smallest market capitalization and S5 is the quintile portfolio of stocks with the largest market capitalization. Within each size quintile, IV1 is the quintile portfolio of stocks with lowest IV and IV5 is the quintile portfolio of stocks with the highest IV. We construct all the portfolios with the value weighting scheme. The excess portfolio return is the difference between the portfolio return and the risk-free rate. MKT is the excess market return; SIZE is the size factor in the Fama and French (1996) 3-factor model; and IVF is the return difference between low and high IV stocks. We calculate t-statistics using the heteroskedasticity-consistent standard error.

Table 12 Diagnostic Tests Using international IV Portfolios: 1973Q1 to 2003Q4

	Prices of Risk (b)			Risk premium (Λ)			J-test	HJ-Dist
	MKT	SMB	IVF	MKT	SMB	IVF		
				Panel A Identity Weighting Matrix				
1	6.236	-1.898	5.269	0.031	-0.002	0.051		0.066
	(3.394)	(-0.22)	(1.843)	(1.960)	(-0.06)	(2.162)		(0.867)
				Panel B HJ Weighting Matrix				
2	4.324	-1.413	4.189	0.016	0.001	0.043		6.850
	(2.981)	(-0.28)	(3.067)	(1.408)	(0.051)	(2.570)		(0.815)
				Panel C Optimal Weighting Matrix				
3	4.902	0.243	4.283	0.017	0.009	0.051	8.507	
	(3.717)	(0.053)	(3.424)	(1.462)	(0.458)	(3.014)	(0.579)	

Note: We estimate the stochastic discount factor models using 14 portfolios of stocks with either highest or lowest IV selected from the 35 international portfolios sorted by IV, as discussed in Table 7. In particular, for each of G7 countries, we select the quintile of stocks with the highest IV and the quintile of stocks with the lowest IV. The law of one price implies the existence of a stochastic discount factor, m_{t+1}, such that

$$E_t(m_{t+1}R_{j,t+1}) = 0 ,$$

where $R_{j,t+1}$ is the excess return on the portfolio *j* at time *t*+1. We assume that the stochastic discount factor is approximately a linear function of the proposed risk factors, F_{t+1}:

$$y_{t+1} = b_0 + b'F_{t+1} ,$$

where the coefficients b' are prices of risk. The linear stochastic discount factor model has an equivalent beta pricing model representation:

$$E(R_j) = \beta_j'\Lambda ,$$

where β_j' is a vector of the loadings of the portfolio *j* on the risk factors, $\Lambda = -R^0 \operatorname{cov}(F, F')b$ is a vector of the risk premia; and R^0 is the risk-free rate or the return on a zero-beta asset. We estimate the model using Hansen's (1982) general method of moments (GMM). For robustness, we consider 3 commonly used weighing matrices: The identity weighting matrix; the inverted covariance matrix of the portfolio returns, as advocated by Hansen and Jagannathan (1997); and the optimal weighting matrix proposed by Hansen (1982). For the first two weighting matrices, we test the model's goodness of fit 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. MKT is the excess market return; SMB is the size factor in the Fama and French (1996) 3-factor model; and IVF is the return difference between low and high IV stocks. All factors are constructed using U.S. data.