The Low-Volatility Anomaly: Market Evidence on Systematic Risk versus Mispricing

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Abstract
We explore whether the well-publicized anomalous returns associated with “low-volatility” portfolios can be attributed to market mispricing or to compensation for higher systematic risk. Our results, conducted over a 46 year study period (1966-2011), indicate that the high excess returns related to long-short "low-volatility" portfolios cannot be viewed purely as compensation for systematic factor risk. We find that the excess returns may be driven more by some market mispricing connected with volatility as a stock characteristic.

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The Low-Risk Anomaly: Market Evidence on Systematic Risk versus Mispricing

In what is sometimes collectively referred to as the “low-volatility” anomaly, researchers have discovered a provocative long-term connection between future stock returns and various measures of prior stock price variability, including total return volatility, idiosyncratic volatility, and beta. More to the point, researchers document that, in both U.S. and international markets, future stock returns of previously low return variability portfolios significantly outperform those of previously high return variability portfolios [see, e.g., Ang, Hodrick, Xing, and Zhang (2006 and 2009), Baker, Bradley, and Wurgler (2011), Clarke, de Dilva, and Thorley (2006), and Blitz and Vliet (2007) and Li, Sullivan, and Garcia-Feijoo (2013)]. These empirical findings are particularly intriguing because, of course, economic theory dictates that higher expected risk is compensated with higher expected return. As such, these findings highlight the need to gain a better understanding of the underpinnings of this curious anomaly. An explanation for its existence, however, remains elusive; more specifically, whether it is driven by some systematic risks or investor mispricing. Our research effort seeks to gain fruitful insight into the low-volatility anomaly. We do so by examining whether this anomaly, which as we will show predominantly comes from the underperformance of the highest volatility stocks, can be largely attributed to market mispricing or to compensation for higher systematic (undiversifiable) risk.

The Low-Volatility Anomaly

With a focus on market beta, Black (1972) offers an early theoretical interpretation of why low risk stocks might do so well relative to high risk stocks. He shows that a delegated agent mispricing arising from borrowing restrictions such as margin requirements might cause low-beta stocks to outperform. More recently, some have argued that the low volatility anomaly is likely due to some pervasive systematic risk factor(s) directly associated with volatility. For example, Clarke, de Silva, and Thorley (2010) suggest that idiosyncratic volatility (and total volatility) is a potential additional risk factor to which portfolio managers should pay attention. The authors find that the excess return to low idiosyncratic volatility stocks is immaterial over the full sample period (1931-2008), suggesting that investors have historically not been rewarded for bearing such risk over the long haul. However, in more recent years (1983-2008) the authors find that exposure to low idiosyncratic volatility stocks has benefitted investors, although the cross-sectional idiosyncratic volatility evidence is weak.

Ang et al., (2009) find existence of an idiosyncratic volatility anomaly in numerous countries, and they further discover that the effect is highly correlated with that in the U.S. They argue that such an effect could be driven by latent systematic risks. Specifically, they show that abnormal returns generated by idiosyncratic volatility-based portfolio strategies in international markets strongly comove with those in the U.S. markets, suggestive of a common risk factor. They state that “The large commonality in co-movement ….suggest that broad, not easily diversifiable factors lie behind this effect.” The co-movement finding suggests that the return predictive power of idiosyncratic risk is likely due to some pervasive risk factor.

Still others offer that the low-volatility anomaly is likely due instead to mispricing as perhaps associated with an imperfection such as investor irrationality connected with idiosyncratic volatility. In the case of mispricing, the profit opportunity may be ephemeral as investors come to understand their cognitive error and arbitrage away any excess return. Or it could be a more lasting mispricing, supported over time by high costs associated with arbitraging away the anomalous returns. For instance, Li, Sullivan, Garcia-Feijoo (2013) show that the efficacy of trading the low-volatility factor is rather limited due to high costs to arbitrage (e.g., high transactions costs) directly associated with attempting to extract the anomalous excess returns.

Perhaps the anomalous effect is supported by some behavioral considerations. Similar to Black (1972), Baker, Bradley, and Wurgler (2011) propose an explanation consistent with biases originating in investor behavior as based on a delegated asset management model. They show that institutional client mandates discourage arbitrage activity that would otherwise potentially eliminate the low-volatility effect.

Merton (1987) offers an interesting explanation for why investors would demand higher returns for taking on higher idiosyncratic risk. He explains that idiosyncratic risk would be positively related to expected return when investors cannot fully diversify their portfolio. That is, investors demand higher compensation from firms with higher idiosyncratic volatility to compensate for imperfect diversification. Interestingly, the empirical evidence in Ang et al., (2009) and Clarke et al., (2010) runs counter to Merton's (1987) prediction.[1] Collectively, these findings highlight the importance of a formal investigation into answering the underlying economic question of whether the various low-risk effects are associated with market mispricing or systematic risks.

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[1] Recent research questions the existence of the negative relationship between idiosyncratic volatility and subsequent returns as reported in Ang et al. (2006, 2009) can be a proxy for some existing anomalies. For example, Fu (2009) and Huang, Liu, Rhee, and Zhang (2010) show that the return association is mostly due to how Ang et al (2006) measure idiosyncratic volatility and that the Ang et al approach essentially captures a large return reversal effect. Also, Fu (2009) shows that the idiosyncratic volatility forecast from an EGARCH model is significantly positively related to subsequent returns. Finally, Bali and Cakici (2008), through a variety of different measures of IVOL, show no significant relationship between IVOL and expected returns.

In our investigation, we do not debate whether previously low volatility stocks may empirically explain future returns. Rather, we ask whether there really is a pervasive systematic factor directly associated with return variability. As such, we aim to shed light on the outperformance of securities with low idiosyncratic volatility, a phenomenon reported in Ang, et al (2006, 2009). Put differently, it is possible that the abnormal returns that researchers have documented to low volatility portfolios could be due to these portfolios having exposure to some not yet understood common risk component. For instance, high-volatility stocks may possess consumption hedging benefits by performing better during weak economic conditions. Theoretically, investors are willing to pay more for those stocks with such hedging benefits. By contrast, investors will only buy low-volatility stocks if they offer a higher expected return, given that their (not yet well understood) exposure to systematic risk causes them to deliver poor returns when cash flows are most valued by investors (e.g., during recessions). Alternatively, investors may exhibit some preference towards high-volatility stocks relative to low volatility stocks, perhaps due to some cognitive biases or some other not yet understood reason.[2]

To investigate which of these two explanations most likely explains the low risk effect, we investigate whether the low-risk anomaly represents returns to some not yet identified risk factor, or whether it is related instead to the characteristic of low-risk itself [e.g., Daniel and Titman (1997, 1998), Daniel, Titman, and Wei (2001), Cohen and Polk (1995), Davis, Fama, and French (2000), and Grundy and Martin (2001)].

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[2] An intriguing risk-based explanation is offered by Cowan and Wilderman (2012), who suggest that low risk stocks trade at a premium to high risk stocks due to the asymmetry in returns during up markets and down markets. They suggest that, versus their high-risk counterparts, low-beta stocks provide essentially equivalent downside market protection but much less upside potential. That is, high-beta stocks provide more upside potential while suffering roughly in line with low-beta stocks in market downdrafts. Thus, low-risk stocks must offer an additional expected return to entice investors to participate.

These researchers have applied specific test methods to identify the source of well-known anomalies such as size, book-to-market, and momentum. We rely on these same methodologies in our examination of the low-volatility anomaly to test whether the previously identified differential returns between high and low volatility stocks can be attributed to factor loadings and/or firm characteristics. In other words, we seek to empirically determine whether the low volatility anomaly is associated with a mispricing or some pervasive systematic risk. In the language of Daniel and Titman (1997, 1998), we perform characteristics versus covariances tests.[3] Through such tests, we are able to examine whether variation in the loadings on a factor created on the basis of volatility, in the fashion of Fama and French (1993), is able to explain future stock returns after controlling for actual return variability.

More specifically, when considering the low volatility anomaly, for the systematic risk explanation to be valid, those stocks with a high factor loading on the low-volatility factor should outperform as compared to those stocks with a low factor loading on the low-volatility factor. This pattern should be observed irrespective of the absolute level of stock volatility. If however, after controlling for the observed level of return variability, loadings on the low-volatility factor are unable to explain cross-sectional stock returns, then we can reasonably conclude that the low-volatility anomaly is consistent with market mispricing.

However, we do not intend to identify the specific source of any possible latent systematic risk or offer explanations for any market mispricing. One attraction of the asset pricing methodologies done in the spirit of Daniel and Titman (1997, 1998) is that they allow researchers to be agnostic about the specific sources of the anomalous effect. For example, if an anomaly is truly due to systematic risk, this approach would still be able to capture and attribute the latent systematic risks to the anomaly, even if the source of the systematic risk are unknown (i.e., not among those already identified by the prior literature).

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[3] These methods employ cross-sectional tests combining characteristic and factor modeling. Pure factor analysis identifies time-series covariation in returns between the factors under study but does not allow us to infer the source of those returns. On the other hand, cross-sectional analysis seeks to reveal characteristics, or attributes, which correspond to those returns.

As we present later, our results indicate that the low volatility anomaly is not due to systematic risk, and that there is no return premium associated with a factor formed on the basis of volatility. This suggests that the abnormal returns identified in the prior literature cannot be viewed as compensation for systematic risk. Put differently, we find that it is the pricing of the characteristic itself which can better explain the outperformance of low-volatility stocks.

Our findings provide insight into the well-documented excess return related to various low-risk anomalies in turn enabling investors to improve portfolio construction and risk management via a deeper understanding of the source of the anomalous returns through time and across firms. In the next section, we draw heavily on the rigorous methods found in the asset pricing literature to shed light on whether the return predictive power of idiosyncratic risk derives from systematic risks or mispricing.

Data and Sample

We obtain stock return data from the Center for Research in Security Prices (CRSP) for all stocks trading on NYSE, AMEX, and Nasdaq for the 1963 through 2011 period. For delisted firms, the CRSP monthly return file does not include the returns from the delisting month unless the delisting date is at the month end. We fetch the returns in the delisting month and the market cap on the delisting date from CRSP daily return file and combine these returns with the delisting returns to create the effective delisting month returns. However, if the delisting is for performance-related reasons, we set the delisting return equal to -55% if trading on Nasdaq or -30% if on NYSE/Amex (see analysis of CRSP delisting bias in Shumway (1997) and Shumway and Warther (1999)).

We follow the most recent literature by focusing attention on idiosyncratic volatility, which studies have shown is negatively associated with subsequent stock returns. We measure idiosyncratic volatility (IVOL) as the standard deviation of the residual returns from the Fama-French three-factor model by regressing the daily returns of individual stocks in excess of the one-month T-bill rates, $R_{i,t} - R_{f,t}$, on the returns to the common factors related to size and book-to-market. In other words, for each stock i we perform the following time series regressions:

$$R_{i,t} - R_{f,t} = a_i + b_i \, (R_{M,t} - R_{f,t}) + s_i \, \mathrm{SMB}_t + h_i \, \mathrm{HML}_t + \varepsilon_{i,t}$$

Where, $R_{M,t} - R_{f,t}$, SMB, and HML constitute the Fama-French market, size and value factors, respectively. We require a minimum of 15 observations for model estimation. With this requirement we omit the most illiquid of stocks from our results, thus minimizing the likelihood that our results are biased towards those stocks that trade infrequently. We correlate the idiosyncratic risk from the current month with the subsequent monthly returns (inclusive of dividends).

We construct the IVOL-based factor as a zero-investment factor mimicking portfolio following Fama and French (1993) and Daniel and Titman (1997). More specifically, at the end of each month, we sort stocks into size (market cap) terciles using NYSE breakpoints; and we sort stocks into terciles based on the IVOL characteristic. We obtain value-weighted monthly returns on a total of nine portfolios: Three size portfolios for each of the three portfolios based on the IVOL characteristic. We then equally weigh each IVOL portfolio across the size terciles to obtain returns on three IVOL portfolios that are size independent. In order to calculate the returns on the zero-cost portfolio representing the IVOL-based factor, we subtract the monthly return on the high-IVOL portfolio from the low-IVOL portfolio.

To estimate factor loadings (betas) on the IVOL factor, we follow the approach used by Daniel and Titman (1997, 1998). Specifically, we conduct rolling regressions of monthly excess stock returns on the Fama-French (1993) three factors plus the IVOL factor over the previous 36 months (24 months minimum). However, the portfolio weights of the factor portfolios used in the rolling regressions are constant based on factor weights each month. That is, the portfolio weights of the factors each month t are applied to returns from date t-37 to t-1 to calculate the returns of constant weight factor portfolios. Estimated loadings on the IVOL factor are pre-formation IVOL betas (��$_{\mathrm{IVOL}}$). If covariances are stationary over time, factor loadings

estimated this way should be good predictors of future betas on the IVOL factor. We present evidence in a later section that confirms this is indeed the case. We obtain IVOL factor betas for the period January 1966 through December 2011 (552 months).

Our approach allows us to separate low IVOL stocks with high and low loadings on the IVOL factor. If the risk-based explanation for the higher observed returns of low-IVOL stocks is correct, then a low-IVOL stock with a low IVOL factor loading should have a low average return. In contrast, if characteristics rather than factor loadings determine prices, a low-IVOL stock should have a high stock return regardless of its loading.

Tests and Results

In Table 1, we begin with reporting summary statistics for the relevant variables including a correlation matrix. In the lower panel of Table 1, it can be seen that the absolute correlation between the IVOL factor and the other portfolio characteristics are moderately high to high. We note that the IVOL factor is negatively contemporaneously related to the market return (-0.56), indicating that when low-IVOL outperform high-IVOL stocks (i.e., the IVOL factor is positive), market returns are low; conversely, high-IVOL stocks outperform when market returns are high.

As part of our analysis, we later form quintile portfolios based on IVOL factor betas (i.e. exposure to IVOL risk). The correlation between the IVOL factor and the difference between the returns on the high- and low-quintiles of ��$_{\mathrm{IVOL}}$ stocks is a

positive 0.68. That is, stocks with a high exposure to a possible source of systematic risk outperform when the risk factor premium is high. The correlation between the IVOL factor and the difference between the high- and low-quintile based on market beta (��$_{\mathrm{CAPM}}$) is a negative -0.79. Additionally, the difference between the high- and low-quintiles based on ��$_{\mathrm{IVOL}}$ has a correlation of -0.71 to the difference between high- and low-��$_{\mathrm{CAPM}}$ quintiles.[4] The negative sign likely occurs by construction (the IVOL factor is low minus high in order to measure a risk premium).

The relatively high absolute correlations in Table 1 are not surprising. Measures of stock return variability are likely to be correlated, and the summary statistics reported in Table 1 do not control for important firm characteristics, such as market capitalization. In the next sections, we conduct a variety of analyses designed to disentangle the effects of IVOL risk from other well-known factors.

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[4] Market or CAPM betas are estimated using the market model where the dependent variable is firm-level monthly excess stock returns, and the market index is the CRSP value-weighted index over the prior 36 months (minimum of 24 months).

In Figure 1, we plot the cumulative stock returns on the market (from Kenneth French's website) and the zero-cost IVOL factor, which is adjusted for the well-known size affect as described above. As can be seen from Figure 1, the IVOL factor outperforms the market portfolio during market declines, and has tended to underperform during rising markets, especially during the current decade.

[Figure 1 here]

In Table 2, we provide further descriptive information for our key variables as sorted into quintiles based on the IVOL characteristic. The sample period is 1966-2011. "EWRet" and "VWRet" represent the average raw returns for equal-weighted and value-weighted quintile returns, respectively. "IVOL" is computed as the IVOL from regressions of excess returns on the Fama-French three factors using daily observations (minimum of 15 days) then multiplied by the square root of the number of trading days in a month, so as to convert it to a monthly measure. As can be observed, average value weighted returns (VWRet) decline when moving from the lowest IVOL quintile to the highest quintile, a finding consistent with the notion that low risk stocks outperform high risk stocks, on average. From Table 2, it can be seen that the so-called low-volatility effect comes mainly from the highest IVOL quintile of the IVOL portfolios having significantly lower return than the other lower-IVOL quintiles, all demonstrating similar returns. We note that this finding suggests the effect may be due to some investors excessively bidding up the price of high volatility stocks. More specifically, the lowest IVOL quintile shows VWRet of 0.88 percent per month and the highest IVOL quintile 0.24 percent per month. However, from column 2 of Table 2, we see that on an equal weighted (EWRet) market return basis, the lowest

IVOL quintile stocks performance at 1.14 percent per month is lower than the other quintiles, rising to 1.78 percent for the highest IVOL quintile. These findings are consistent with prior research (e.g., Li, Sullivan, Garcia-Feijoo (2012)).

Not surprisingly, monthly idiosyncratic volatility (the ranking variable) increases from the lowest to the highest quintile. Average market betas also increase, which indicates both measures of risk are positively associated. In the last column of Table 2, there is evidence of a negative unconditional association between IVOL (the quintile characteristic) and ��$_{\mathrm{IVOL}}$. Specifically, the average ��$_{\mathrm{IVOL}}$ is 0.13 for the lowest and -0.31 for the highest quintile. This is important because for us to be able to distinguish between risk and mispricing as possible explanations for the low-IVOL anomaly, there needs to be dispersion in ��$_{\mathrm{IVOL}}$ that is unrelated to IVOL as a characteristic. Next, we probe more deeply into the potential underpinnings of the low risk anomaly.

Cross-Sectional Regressions

We begin our formal investigation by applying an extension of the monthly Fama-MacBeth (1973) cross-sectional regressions in which we regress individual stock returns on the loadings on the IVOL factor (��$_{\mathrm{IVOL}}$) and the level of the IVOL characteristic while controlling for the well known size and style effects. Size (ME) is measured as the logarithm of the equity market capitalization obtained at the end of the prior month, and book-to-market (BEME) is measured as the logarithm of one plus the book-to-market ratio of equity (computed as in Fama and French, 1992); we use accounting data for the prior fiscal year and market capitalization as of the end of the prior calendar year.

Table 3 presents the results. Columns (1) and (2) show that both the IVOL characteristic and the loading on the IVOL-factor (β_{IVOL}) are insignificantly related to subsequent stock returns when other variables are not controlled for (t =0.99 and t =-0.31, respectively). Columns (3) and (4) show results when we include the common control variables of size and style. Column (3) shows that β_{IVOL} remains insignificant when including size and style effects. By contrast, Columns (4) and (5) show that the IVOL characteristic can predict subsequent stock returns at the 1% level of significance with the inclusion of other control variables. Columns (1) through (5) report results for the full sample, while columns (6) through (8) report results for three subperiods. In the linear regression analysis, there is evidence of a strong IVOL effect prior to 1990, which disappears in the more recent period. In all of our regressions, β_{IVOL} is never significant. The results from our cross sectional regressions therefore indicate that average subsequent returns over the study period are determined by common variation associated with the IVOL characteristic rather than factor loadings. This analysis suggests that the return predictive power associated with IVOL is best explained by a market mispricing rather than some pervasive risk factor.

In Table 4, we conduct a rank portfolio test in order to further explore the performance of strategies based on the IVOL characteristic and the IVOL-based factor loadings. This test is commonly used to assess whether the return differences generated by the characteristic and factor loading differ across quintiles (i.e. non-linearly). Specifically, we equally assign firms to quintile portfolios according to the magnitude of their prior month's IVOL characteristic or β_{IVOL}. We then calculate the following month's equal-weighted and value-weighted return for each quintile portfolio. We then separately measure the abnormal returns on the quintile spread portfolios, or the difference portfolio between the highest- and lowest-ranked quintiles. We calculate the abnormal returns for each portfolio using the intercept from the Fama-French (1993) three-factor model whose dependent variables are the monthly returns of these portfolios in excess of the risk free rate.[5]

Table 4 shows that sorting solely on ��$_{\text{IVOL}}$ generates insignificant abnormal returns for the equal-weighted and value-weighted quintile portfolios; e.g., the zero-cost spread, or difference, portfolios demonstrate insignificant coefficient estimates. In contrast, sorting solely on the IVOL characteristic generates a significant difference in returns for the value-weighted IVOL characteristic spread portfolio with a significant coefficient estimate of -1.09 (t =-6.67). The equal-weighted spread IVOL characteristic portfolio is insignificant. From the coefficient estimate of the difference portfolios, adjusted for the Fama-French (1993) three-factors, we calculate the implied annualized abnormal monthly value-weighted return to a strategy that goes long low-volatility and goes short high-volatility stocks as 13.89% (= $(1 + 1.09\%)^{12} - 1$).

Double Sorting on Both Characteristics and Factor Loadings

In this section, we form "characteristic-balanced" portfolios in order to test whether the IVOL factor loadings or the IVOL characteristic explain future stock returns. This provides another approach to differentiate the market inefficiency and risk factor explanations. Specifically, each month, we sort stocks into two groups based on prior-month market capitalization (ME) using NYSE breakpoints, and into three groups based on prior-month IVOL characteristic. Within each of the resulting six categories, we assign stocks into quintiles based on (pre-formation) ��$_{\text{IVOL}}$. We compute value-

weighted average returns for each quintile and for the difference between the high and low ��$_{\text{IVOL}}$ quintiles. As noted by Daniel and Titman (1997, 1998), in tests where factors are constructed from characteristics shown to predict returns, the factor loadings may appear to predict stock returns even though their predictive power is not due to systematic risk. This is so because the characteristic and the constructed factor tend to positively correlate. Should the IVOL factor loading explain the cross-section variation of stock returns, as measured by the significance of the quintile spread portfolio returns, then the predictive ability of the IVOL characteristic would likely be due to systematic risk. In contrast, the mispricing hypothesis requires that the IVOL factor loadings have no additional return predicting power associated with the various characteristic-balanced IVOL portfolios.

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[5] We obtain the Fama-French factors ($r_m - r_f$, *SMB*, and *HML*) and risk free rate from Ken French's website.

In Table 5, Panel A, we report the monthly average IVOL characteristic of the stocks in each portfolio. A quick review reveals no differences across the increasing ��$_{IVOL}$ quintiles within each IVOL characteristic and size category. That is, the portfolios in each row are similar in terms of the characteristic but differ in terms of pre-formation ��$_{IVOL}$. In Panel B, we report average post-formation IVOL-factor loads, computed from monthly regressions of excess returns (reported in Panel C) on the Fama-French three factors and the IVOL-factor. The pre-formation estimates forecast future ��$_{IVOL}$ as evidenced by the universal increase in average postformation ��$_{IVOL}$ values as we move up from quintile 1 to quintile 5 for each preformation ��$_{IVOL}$ quintile. That is, the pre-formation sorts generate noticeable differences between the ex-post betas of the high and low ��$_{IVOL}$ quintiles. The important conclusion from panels A and B is that the two extreme ��$_{IVOL}$ quintiles are different in terms of ex-post beta exposure but not in terms of the IVOL characteristic. Although not shown, the differences are larger in terms of pre-formation betas.

In Table 5, Panel C, we report value-weighted excess stock returns on the 30 portfolios.[6] In each row, as we move from left to right, portfolios increase in risk as measured by ��$_{\text{IVOL}}$ but do not differ in terms of characteristics (IVOL and size). If the low volatility "effect" is due to systematic risk, we would expect stock returns to be significantly higher for high ��$_{\text{IVOL}}$ portfolios. However, the insignificant results shown in the right most column, which subtracts the average returns on the low ��$_{\text{IVOL}}$ from the high ��$_{\text{IVOL}}$ quintile, indicates returns are not related to exposure to the IVOL factor, after controlling for characteristics. In the last row of Panel C, we report the returns of a strategy that goes long high IVOL stocks and short low IVOL stocks of equal size. We focus on small stocks because the average monthly number of stocks in the High-Ivol Big-Size group is only 12. Low-IVOL stocks earn higher excess returns than high-ivol stocks across beta quintiles; significantly so in quintiles 2 through 4.

In Table 5, Panel D, we report abnormal returns (alphas) of the regressions of value-weighted excess returns on the Fama-French three factors plus the IVOL-factor. If the low volatility effect is due to systematic risk, abnormal returns should be zero after adjusting for factor risk. By contrast, if the effect is due to the characteristic, mean returns would be independent of variation in the factor loadings; hence alphas would tend to be positive for low ��$_{\text{IVOL}}$ portfolios because the factor model would predict lower returns than realized on average, and alphas would tend to be negative for high ��$_{\text{IVOL}}$ portfolios because the factor model would predict higher returns than realized on average. As shown in Panel D, alphas tend to be positive for the low ��$_{\text{IVOL}}$ portfolios, and negative for the high ��$_{\text{IVOL}}$ portfolios, though alphas are often insignificant.

However, as our earlier results from Table 3 indicate, there was a strong low-IVOL effect in the 1966-1989 subperiod, but the effect disappeared post-1990.

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[6] The average monthly number of stocks in each quintile portfolio as we move from the top to the bottom of Table 5 is 155, 102, 205, 51, 246, and 12.

Accordingly, to better understand what underlies the effect, we additionally focus on the early, 1966-1989, period and report the results in Table 6. In Table 6, Panel A, we report value-weighted excess stock returns on the 30 portfolios for the subperiod. Whereas excess returns tend to be positive for the low-ivol portfolios, and negative or zero for the high-ivol portfolios, there is no difference between the returns on the high-��$_{\text{IVOL}}$ and the low- ��$_{\text{IVOL}}$ quintiles. In Table 6, Panel B, we report alphas on the three

factor plus the ivol factor. Consistent with the predictions of the characteristic model (i.e., Daniel and Titman, 1997, 1998), alphas tend to be significantly positive for the low-��$_{\text{IVOL}}$ portfolios, and negative for the high ��$_{\text{IVOL}}$ portfolios. In the right most column, we report alphas on zero-investment portfolios that are "characteristic-balanced" portfolios because each is constructed to have approximately equal IVOL and ME. In the bottom right corner, we report alphas on the "combined portfolio," which is an equal-weighted combination of the six portfolios. If the IVOL effect is due to the IVOL characteristic, the intercepts should be significantly negative, indicating the factor adjustment tends to overestimate the returns on high ��$_{\text{IVOL}}$ stocks and underestimate

the returns on low ��$_{\text{IVOL}}$ stocks. This is, in fact, what the results of table 6 show; all

alphas are negative, two of them significantly so; and the alpha on the combined portfolio is -0.19% (t-stat -1.15), or -0.32% (t-stat -2.14) after the High and Big group, which only has an average of 12 stocks in each quintile, is excluded.

In Figure 2, we plot the cumulative monthly return on the characteristic-balanced portfolio and the factor-balanced portfolio, constructed as in Daniel and Titman (1998) by going long the factors in the amount of the loadings of the characteristic-balanced portfolio and going short the characteristic-balanced portfolio (so the factor loadings on the factor-balanced portfolio are zero).

To summarize, researchers have identified prior stock return idiosyncratic volatility as a surprisingly reliable predictor of returns beyond size and book-to-market effects. Taken together, our research findings suggest that the previously identified excess returns on low idiosyncratic volatility stocks do not arise because of the correlations of these stocks with some pervasive (systematic) factor. Instead, our results indicate that the abnormal returns on low idiosyncratic volatility stocks arise most likely from some market mispricing associated with certain characteristics present in low volatility firms. That is, investors appear to have some particular preference for stocks exhibiting a high volatility characteristic relative to stocks with a low volatility characteristic. Our empirical findings provide additional support for those who conjecture that the low risk anomaly emanates from some investor preferences due perhaps to a behavioral considerations (Baker, Bradley, and Wurgler (2011) and/or some limits to effectively arbitraging away any mispricing (Li, Sullivan, and Garcia-Feijoo (2012). As such, we encourage further research to disentangle the underlying source of excess returns.

Conclusion

Contrary to fundamental expectations, researchers have found that a strategy of buying previously low-volatility stocks and selling previously high-volatility stocks has historically generated substantial abnormal returns in the U.S. and international markets. By asking whether there really are pervasive systematic factors (and thus risk premia) that are directly associated with low volatility firms, we seek to answer a fundamental question related to the so-called “low-volatility” anomaly.

Our analysis adds important insight into whether the anomalous low-risk effects are driven by systematic risks or market mispricing. The asset pricing literature provides diagnostic methods for evaluating the source and mechanisms that are driving a particular anomalous effect. We use these descriptive procedures to examine whether the return patterns of volatility characteristic-sorted portfolios are consistent with a factor model suggesting systematic risk, or whether they are consistent with market mispricing.

Our results indicate that market mispricing best characterizes the linkage between low volatility and future returns. This suggests that the high anomalous returns related to low volatility portfolios identified in prior literature cannot be viewed as compensation for some hidden factor risk. That is, investors appear to have some particular preference for stocks exhibiting a high volatility characteristic relative to stocks with a low volatility characteristic.

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Table 1
Summary Statistics 1966-2011

Variable	IVOL Factor	High β_{IVOL} – Low β_{IVOL}	High β_{CAPM} - Low β_{CAPM}	Rm-RF	HML	SMB
Mean	0.66%	-0.01	0.02	0.41	0.37	0.25
Standard Deviation	5.53	4.43	6.50	4.64	2.98	3.21
Quartile 3	3.02	2.51	3.72	3.56	1.78	2.17
Median	0.63	0.02	-0.26	0.75	0.37	0.07
Quartile 1	-1.62	-2.29	-3.61	-2.31	-1.30	-1.59
Correlations						
IVOL Factor	1.00	0.68***	-0.79***	-0.56***	0.51***	-0.61***
High β_{IVOL} – Low β_{IVOL}		1.00	-0.71***	-0.47***	0.32***	-0.42***
High β_{CAPM} - Low β_{CAPM}			1.00	0.67***	-0.50***	0.51***
Rm-Rf				1.00	-0.31***	0.31***
HML					1.00	-0.23***

We measure idiosyncratic volatility (IVOL) as the standard deviation of the residual returns from the Fama-French three-factor model by regressing the daily returns of individual stocks in excess of the one-month T-bill rates, $R_{i,t} - R_{f,t}$, on the returns to the common factors related to size (SMB) and book-to-market (HML). We require a minimum of 15 observations for model estimation. We correlate the idiosyncratic risk from the current month with the subsequent monthly returns (inclusive of dividends). We construct the IVOL-based factor as a zero-investment factor mimicking portfolio, as follows. At the end of each month, we sort stocks into size (market cap) terciles using NYSE breakpoints, and into terciles based on the IVOL characteristic. We obtain value-weighted monthly returns on a total of nine portfolios: three size portfolios for each of the three portfolios based on the IVOL characteristic. We then equally weigh each IVOL portfolio across the size terciles to obtain returns on three IVOL portfolios that are size independent. In order to calculate the returns on the zero-cost portfolio representing the IVOL factor, we subtract the monthly return on the high-IVOL portfolio from the low-IVOL portfolio. To estimate factor loadings on the IVOL factor (β_{IVOL}) we use the approach of Daniel and Titman (1997, 1998), as follows. We conduct rolling regressions of monthly excess stock returns at the firm-level on the Fama-French (1993) three factors plus the IVOL factor over the previous 36 months (24 months minimum). However, the returns on the factors are based on weights as of month t, for regressions over months t-37 to t-1. The sample period is January 1966- December 2011. Market betas (β_{CAPM}) are estimated using the market model over the prior 36 months (minimum of 24 months); the dependent variable is the firm-level monthly excess stock return, and the market index is the CRSP value-weighted index. Portfolios "High β_{IVOL} – Low β_{IVOL}" (or "High β_{CAPM} - Low β_{CAPM}") refer to the difference in the value weighted returns on the two extreme quantiles portfolios based on β_{IVOL} (or β_{CAPM}). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

Table 2
Risk and Return Characteristics of Idiosyncratic Volatility (IVOL) Portfolios

Ivol Quintile	EWRet (%)	VWRet (%)	Ivol (%)	β_{CAPM}	β_{IVOL}
Low	1.14	0.88	4.37	0.79	0.15
2	1.31	0.92	7.46	1.02	0.06
3	1.41	0.94	10.50	1.20	-0.05
4	1.44	0.83	14.86	1.34	-0.19
High	1.78	0.24	28.22	1.40	-0.31
High-Low	0.64**	-0.64**	23.84***	0.61***	-0.46***
t-stat	2.11	-2.20	49.20	29.44	-34.45

Table 2 reports results for various variables sorted by IVOL quintile over the period 1966-2011 (552 months). EWRet and VWRet are the average raw returns for equal-weighted and value-weighted monthly returns, respectively. Ivol is computed as the idiosyncratic volatility (IVOL) from regressions of excess returns on the Fama-French three factors using daily observations (minimum of 15 days), then multiplied by the square root of the number of trading days in a month, so as to convert it to a monthly measure. The estimation of β_{IVOL} and β_{CAPM} is explained in Table 1. Reported averages are computed as time-series averages of cross-sectional means. Robust Newey-West (1987) t-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 3
Monthly Fama-MacBeth Regressions of
Stock Returns on the IVOL Characteristic and on ��$_{\text{IVOL}}$

	Coeff (%) (t-stat) (1)	Coeff (%) (t-stat) (2)	Coeff (%) (t-stat) (3)	Coeff (%) (t-stat) (4)	Coeff (%) (t-stat) (5)	Coeff (%) (t-stat) (6)	Coeff (%) (t-stat) (7)	Coeff (%) (t-stat) (8)
Variable / Sample Period	1966-2011	1966-2011	1966-2011	1966-2011	1966-2011	1966-1989	1990-2011	1990-2006
Ivol characteristic	1.03% (0.99)			-1.79*** (-2.87)	-1.76*** (-2.90)	-3.83*** (-4.66)	0.60 (0.79)	1.15 (1.29)
��$_{\text{IVOL}}$		-0.02 (-0.31)	0.03 (0.91)		0.02 (0.64)	0.02 (0.43)	0.02 (0.49)	0.06 (1.40)
Log (ME)			-0.17*** (-3.81)	-0.18*** (-4.80)	-0.18*** (-4.85)	-0.17*** (-2.99)	-0.19*** (-4.10)	-0.21*** (-3.87)
Log (BEME)			0.35** (2.41)	0.34** (2.44)	0.33** (2.36)	0.37*** (2.63)	0.28 (1.12)	0.36 (1.26)
��$_{\text{CAPM}}$			0.08 (0.73)	0.09 (0.89)	0.11 (1.08)	-0.01 (-0.11)	0.24 (1.53)	0.14 (0.87)
Intercept	1.13*** (5.21)		1.86*** (4.73)	2.02*** (6.28)	2.02*** (6.22)	2.07*** (4.47)	1.97*** (4.35)	2.20*** (4.57)

Table 3 reports the results of Fama-MacBeth (1973) regressions. Reported coefficient estimates are time-series means of estimated parameters from monthly cross-sectional regressions (in percentage). We measure idiosyncratic volatility (IVOL characteristic), ��$_{\text{IVOL}}$, and ��$_{\text{CAPM}}$ as explained in Table 1. ME is equal to prior-month market capitalization (price times number of shares outstanding); BEME is equal to book equity in the prior fiscal year-end, computed as in Fama and French (1992) divided by market capitalization at the end of the prior calendar year. Stock returns are from CRSP and are adjusted for dividends and delisted returns; accounting variable data are from Compustat. Robust Newey-West (1987) t-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The data are from 1966 through 2011. There is an average of 2,600 observations in each cross-section (minimum 1,055, maximum 3,712).

Table 4
Monthly Fama-French (1993) Factor-Adjusted Returns of Quintile Portfolios

Ranking Variable	IVOL Characteristic		��$_{VO}$	
Weighting	EW	VW	EW	VW
Low	0.19*** (3.49)	0.10%** (2.23)	0.27** (2.34)	-0.08 (-0.72)
2	0.23*** (4.20)	0.02 (0.42)	0.20*** (2.84)	0.63 (1.15)
3	0.25*** (4.63)	-0.03 (-0.43)	0.21*** (3.86)	0.03 (0.64)
4	0.20** (2.52)	-0.25** (-2.56)	0.23*** (4.37)	0.01 (0.24)
High	0.44*** (2.60)	-0.99*** (-7.06)	0.34*** (5.66)	0.07 (0.87)
High-Low	0.25 (1.30)	-1.09*** (-6.67)	0.06 (0.57)	0.15 (0.92)

Table 4 reports the coefficient estimates and t-statistics for the intercept ("alphas") of the Fama-French (1993) three-factor model in percentage. The dependent variables are the monthly excess returns of equal-weighted (EW) and value-weighted (VW) quintile portfolios formed monthly by assigning firms into quintiles based on the magnitude of the prior month's IVOL characteristic and IVOL factor loadings (��$_{IVOL}$). Stock returns adjusted for dividends and delisting are from CRSP and accounting variables are from Compustat. Heteroscedasticity-consistent t-statistics [White (1980)] measuring the significance of excess returns are in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The data are from 1966 through 2011.

Table 5
Factor-Adjusted Portfolio Returns from Independent Sorts on the IVOL Characteristics and the IVOL-Based Factor Loadings

Panel A. Average of Monthly IVOL

		Preformation β_{IVOL}				
IVOL Rank	Size Rank	1	2	3	4	5
Low	Small	5.63	5.38	5.30	5.39	5.51
Low	Big	5.84	5.46	5.31	5.28	5.46
Medium	Small	10.96	10.68	10.55	10.54	10.70
Medium	Big	10.43	10.02	9.91	9.82	9.92
High	Small	24.92	23.27	22.62	22.52	23.78
High	Big	18.95	18.45	18.02	17.68	17.41
Average		12.79	12.21	11.95	11.87	12.13

Panel B. Average of Postformation ��$_{\text{IVOL}}$

		Preformation β_{IVOL}				
IVOL Rank	Size Rank	1	2	3	4	5
Low	Small	0.21	0.27	0.27	0.30	0.30
Low	Big	0.02	0.12	0.17	0.20	0.18
Medium	Small	-0.15	0.05	0.15	0.16	0.10
Medium	Big	-0.41	-0.13	-0.09	0.02	0.00
High	Small	-0.79	-0.46	-0.28	-0.25	-0.27
High	Big	-1.18	-0.98	-0.68	-0.49	-0.54
Average		-0.25	-0.19	-0.08	-0.01	-0.04

Panel C. Value-weighted Average of Monthly Excess Returns

		Preformation β_{IVOL}					
IVOL Rank	Size Rank	1	2	3	4	5	5-1
Low	Small	0.80%*** (3.47)	0.84*** (4.26)	0.83*** (4.43)	0.87*** (4.49)	0.82*** (4.11)	0.02 (0.16)
Low	Big	0.60*** (2.66)	0.40** (2.13)	0.45** (2.52)	0.38** (2.16)	0.47*** (2.60)	-0.13 (-0.90)
Medium	Small	0.90*** (2.76)	0.81*** (2.94)	0.90*** (3.53)	0.90*** (3.48)	0.85*** (3.19)	-0.05 (-0.39)
Medium	Big	0.61* (1.91)	0.58** (2.19)	0.49* (1.92)	0.34 (1.46)	0.33 (1.34)	-0.28 (-1.38)
High	Small	0.32 (0.75)	0.35 (0.94)	0.35 (1.08)	0.41 (1.25)	0.49 (1.45)	0.17 (0.92)
High	Big	-0.33 (-0.69)	-0.31 (-0.75)	-0.16 (-0.42)	0.02 (0.06)	0.40 (1.12)	0.73* (1.95)
Average		0.49	0.44	0.48	0.49	0.56	0.07 (0.57)
High Small – Low Small		-0.48 (-1.64)	-0.49** (-2.02)	-0.47** (-2.29)	-0.46** (-2.32)	-0.32 (-1.49)	

Panel D. Alphas on three factors plus Ivol factor

		Preformation β_{IVOL}					
IVOL Rank	Size Rank	1	2	3	4	5	5-1
Low	Small	-0.05 (-0.64)	-0.02 (-0.31)	0.01 (0.11)	0.01 (0.14)	-0.04 (-0.60)	0.02 (0.17)
Low	Big	0.16* (1.77)	-0.09 (-1.39)	-0.04 (-0.68)	-0.12 (-1.59)	-0.05 (-0.55)	-0.21 (-1.55)
Medium	Small	0.20** (1.96)	-0.01 (-0.13)	0.05 (0.60)	0.03 (0.39)	0.04 (0.56)	-0.16 (-1.40)
Medium	Big	0.41*** (2.65)	0.19 (1.68)	0.07 (0.65)	-0.12 (-1.18)	-0.14 (-1.18)	-0.55*** (-2.67)
High	Small	0.11 (0.73)	-0.14 (-1.20)	-0.23** (-2.40)	-0.20** (-2.13)	-0.07 (-0.68)	-0.19 (-1.17)
High	Big	-0.17 (-0.60)	-0.16 (-0.70)	-0.18 (-0.85)	-0.19 (-0.81)	0.32 (1.45)	0.49 (1.30)
Average		-0.03	-0.04	-0.05	-0.10	0.01	
High Small – Low Small		0.17 (-0.98)	-0.12 (-0.99)	-0.24** (-2.23)	-0.21** (-1.96)	-0.03 (-0.28)	

Table 5 reports value-weighted monthly excess returns (in percentage), idiosyncratic volatility, and the intercept (in percentage) and β_{IVOL} estimates of time series regressions of the value-weighted excess returns on the Fama-French (1993) three factors plus the IVOL-based factor. Each month, we sort stocks into two groups based on prior-month market capitalization (ME) using NYSE breakpoints, and into three groups based on prior-month IVOL characteristic. Within each of the resulting six categories, we assign stocks into quintiles based on (pre-formation) β_{IVOL}. Robust Newey-West (1987) t-statistics from the time series of portfolio returns are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The data are from 1966 through 2011. The average monthly number of stocks in each quintile portfolio as we move from the top to the bottom of the table is 155, 102, 205, 51, 246, and 12.

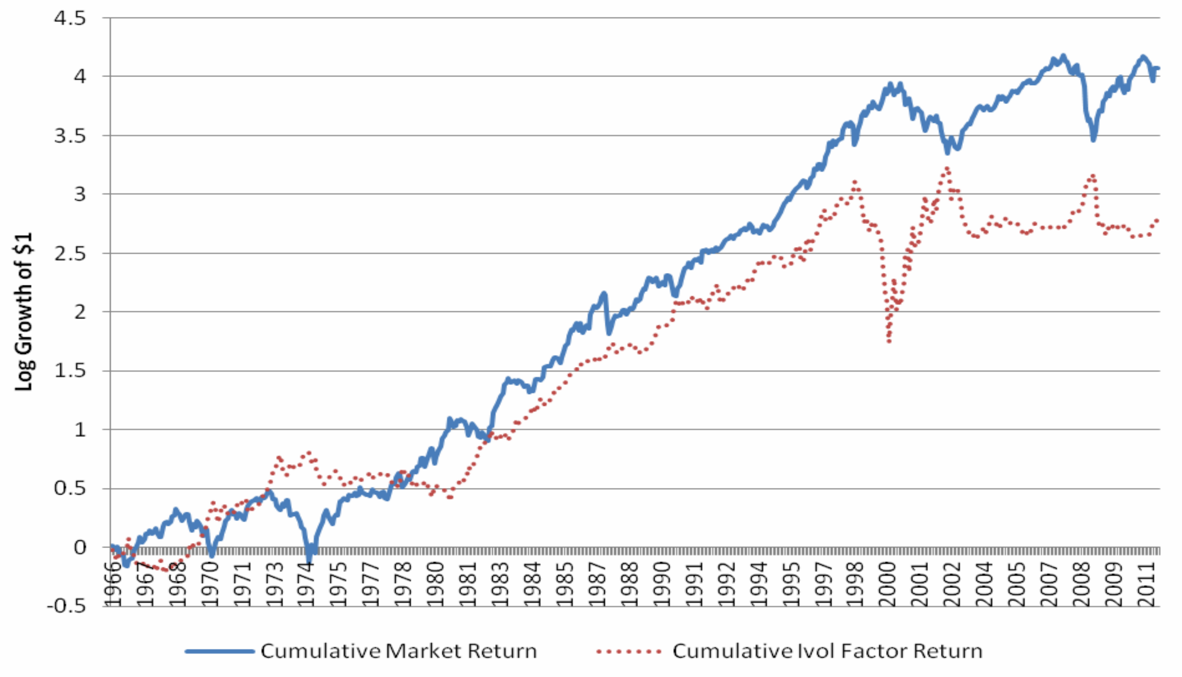
Table 6
Regression Results for the Characteristic-Balanced Portfolios in the Subperiod 1966-1989

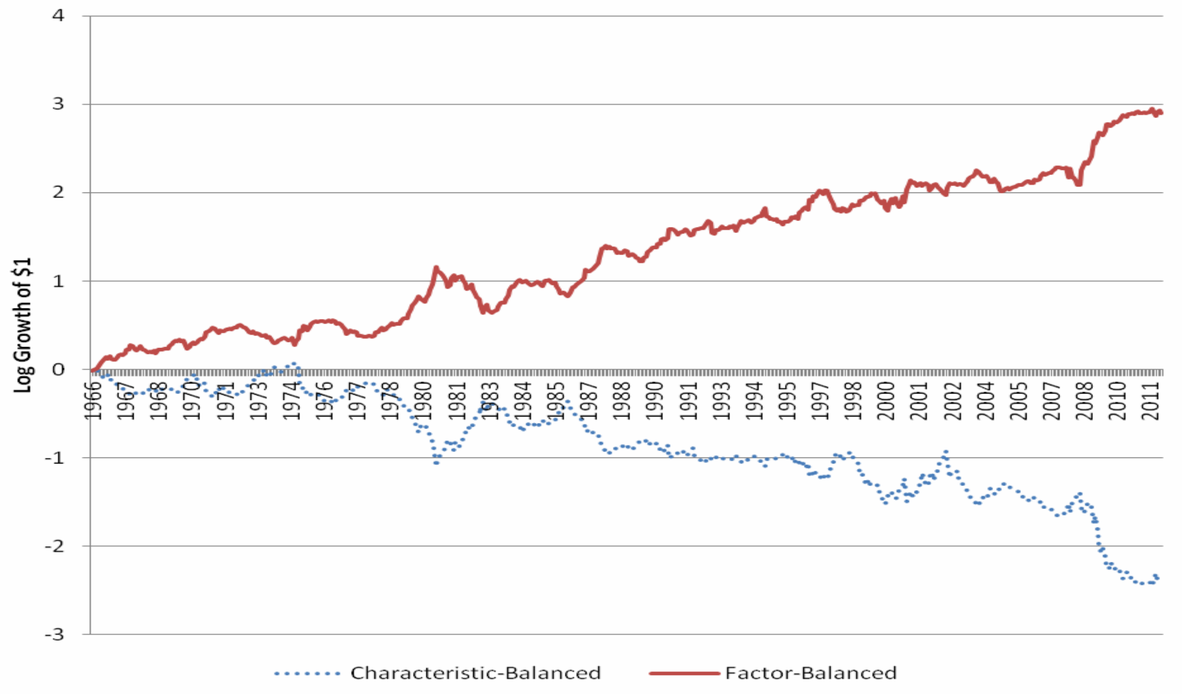
Panel A. Value-weighted Average of Monthly Excess Returns							
		Preformation β_{IVOL}					
IVOL Rank	Size Rank	1	2	3	4	5	5-1
Low	Small	0.82%** (2.49)	0.80*** (2.86)	0.70*** (2.63)	0.87*** (3.13)	0.79*** (2.74)	-0.04 (-0.33)
Low	Big	0.42 (1.36)	0.30 (1.09)	0.34 (1.32)	0.25 (0.99)	0.28 (1.14)	-0.13 (-0.71)
Medium	Small	0.79* (1.79)	0.78** (2.01)	0.90** (2.46)	0.89** (2.38)	0.84** (2.20)	0.05 (0.34)
Medium	Big	0.34 (0.85)	0.47 (1.33)	0.51 (1.55)	0.45 (1.42)	0.35 (1.06)	0.01 (0.05)
High	Small	-0.12 (-0.23)	-0.06 (-0.13)	0.18 (0.42)	0.11 (0.25)	0.16 (0.37)	0.28 (1.31)
High	Big	-0.72 (-1.41)	-0.61 (-1.29)	0.01 (0.03)	0.21 (0.49)	0.19 (0.47)	0.91** (2.38)
Average		0.25	0.28	0.44	0.46	0.43	0.18 (1.13)
Average excluding High and Big		0.45	0.46	0.52	0.51	0.48	0.03 (0.23)

Panel B. Alphas on three factors and Ivol factor							
		Preformation β_{IVOL}					
IVOL Rank	Size Rank	1	2	3	4	5	5-1
Low	Small	0.09% (1.04)	-0.05 (-0.60)	-0.12 (-1.60)	-0.02 (-0.27)	-0.06 (-0.86)	-0.16 (-1.26)
Low	Big	0.27** (2.39)	-0.11 (-1.23)	-0.08 (-0.78)	-0.28*** (-2.61)	-0.25** (-1.96)	-0.52** (-2.51)
Medium	Small	0.27** (2.27)	0.17* (1.80)	0.27*** (3.35)	0.20** (2.40)	0.10 (1.04)	-0.17 (-1.16)
Medium	Big	0.52*** (2.98)	0.46*** (3.36)	0.15 (1.44)	0.03 (0.26)	-0.08 (-0.55)	-0.61** (-2.19)
High	Small	-0.30** (-1.97)	-0.37*** (-3.12)	-0.26** (-2.40)	-0.41*** (-3.87)	-0.46*** (-4.00)	-0.16 (-0.79)
High	Big	-0.41 (-1.35)	-0.13 (-0.50)	0.35 (1.24)	-0.03 (-0.12)	0.07 (0.28)	-0.48 (-1.11)
Average		0.07	-0.01	0.05	-0.09	-0.35	-0.19 (-1.15)
Average excluding High and Big		0.17	0.02	-0.01	-0.10	-0.32	-0.32** (-2.14)

Table 6 reports value-weighted monthly excess returns (in Panel A) and the intercepts and t-statistics (in Panel B) from time-series regressions of excess returns on the Fama-French (1993) three factors and the Ivol factor, which is constructed as described in Table 1. The sample period is 1966-1989, which is when the low ivol effect is strongest. The alphas for the 5-1 zero-investment portfolios reported in the bottom right corner are based on the combined characteristic-balanced portfolio, which is an equal weighted average of the 5-1 zero-investment returns generated from each of the six categories by subtracting the returns on the 1st quintile (i.e., low ��$_{\text{IVOL}}$) from the and 5th quintile (i.e., high ��$_{\text{IVOL}}$).

Figure 1. Cumulative Monthly Returns on the Market and the Ivol Factor



Figure 2. Cumulative Stock Returns on Characteristic-Balanced and Factor-Balanced Portfolios