Why Low-Volatility Stocks Outperform: Market Evidence on Systematic Risk versus Mispricing

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Abstract
We explore whether the well publicized anomalous returns associated low-volatility stocks can be attributed to market mispricing or to compensation for higher systematic risk. Our results, conducted over a 46 year study period (1962- 2008), indicate that the high returns related to low-volatility portfolios cannot be viewed as compensation for systematic factor risk. Instead, the excess returns are more likely to be driven by market mispricing as perhaps associated with an imperfection such as some investor irrationality connected with volatility.

Why Low-Volatility Stocks Outperform: 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 (2010), Clarke, de Dilva, and Thorley (2006), and Blitz and Vliet (2007)]. 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. To date, however, only a few have offered an explanation for its existence; 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 can be attributed to market mispricing or to compensation for higher systematic (undiversifiable) risk.

In making this differentiation, we address a fundamental issue for investors. Should the anomaly be related to systematic risk, then the excess returns can be viewed as arising from some, as of yet unknown, common risk factor(s). Alternatively, it may be driven by a mispricing, as perhaps associated with an imperfection such as investor irrationality connected with volatility. The importance of these issues bolsters our formal investigation into answering the underlying question of whether the documented low-volatility effects are associated with some market mispricing or (as of yet unidentified) pervasive systematic risks. Though, in this paper we focus our discussion on the well-known idiosyncratic risk factor, we not surprisingly find similar results for total volatility.

The Low-Volatility Anomaly

With a focus on market beta, Black (1972) offers an early theoretically consistent 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 commove 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 and Sullivan (2010) show that the efficacy of trading the low-volatility factor is very limited due to high transactions costs directly associated with attempting to extract the anomalous excess returns.

Perhaps the anomalous effect is also supported by some behavioral considerations. Similar to Black (1972), Wurgler, Baker, and Bradley (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 some market mispricing or some pervasive systematic risks.

In our investigation, we do not debate the supposition whether previously low volatility stocks may empirically explain future returns. Rather, we ask whether there really are pervasive systematic factors that are directly associated with return variability. Specifically, we follow methodologies found in the asset pricing literature (e.g., Daniel and Titman (1997)) to test whether the previously identified differential returns between high and low volatility stocks can be attributed to their factor loadings and/or certain firm characteristics. This frequently used approach allows us to empirically determine if the low volatility anomaly is associated with a mispricing or some pervasive systematic risk.

We also do not intend to identify the source of any possible latent systematic risks or offer explanations for market mispricing. One attraction of the asset pricing methodologies done in the spirit of Daniel and Titman (1997) 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 risks, this approach would still be able to capture and attribute the latent systematic risks to the anomaly, even if the

[1] Recent research suggests that 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 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.

source of the systematic risks are unknown (i.e., not among those already identified by the prior literature).

Our results indicate that the low volatility anomaly is not due to systematic risks, 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. 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.

Identifying the Source of Abnormal Returns

In traditional asset pricing, as described by CAPM, expected returns are determined by beta, or covariance with the market. However, additional variables such as size and book-to-market have been found that reliably predict returns but have little relationship to market beta. There is, however, considerable disagreement about the reason for the excess returns of size and book-to-market effects. Some (e.g., Fama and French (1993, 1996)), suggest that the higher returns are compensation for higher risk associated with systematic factors directly associated with size and book-to-market. In contrast, others (e.g., Lakonishok, Shliefer, and Vishney (1994)) and Daniel and Titman (1997)), suggest that the higher returns are likely associated with market mispricing. For instance, they suggest the book-to-market effect may be driven by investors placing too high expectations on earnings growth rates of low book-to-market firms, perhaps due to excessive optimism in extrapolating future returns for such firms that have done well historically.

Accordingly, the asset pricing literature provides diagnostic procedures for evaluating whether the return predictive power of a certain anomaly can be traced to systematic risks or market mispricing [e.g., Daniel and Titman (1997), Daniel, Titman, and Wei (2001), Cohen and Polk (1995), Davis, Fama, and French (2000), and Grundy and Martin (2001)]. These researchers have applied these test methodologies 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. In the language of Daniel and Titman (1997), we perform characteristics versus covariances tests.[2] Through such tests, we are able to examine whether variations in the loadings on factors created on the basis of volatility, in the fashion of Fama and French (1993), after controlling for actual return variability, are still able to explain future stock returns. A particular factor loading provides an estimate of that factor's risk premium. Thus, when considering the low volatility anomaly, for the systematic risk explanation to be valid, those stocks with a low factor loading on the low-volatility factor would necessarily have higher stock returns as compared to those stocks with a high factor loading. 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-

[2] 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.

sectional stock returns, then we can reasonably conclude that the low-volatility anomaly is consistent with some market mispricing.

Data and Sample

We obtain stock return data from the Center for Research in Security Prices (CRSP) monthly stock returns files for the 1962 through 2008 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. For stocks whose delisting returns are missing on CRSP, we set the delisting return to -100%.

We follow the most recent literature by focusing attention on idiosyncratic volatility. Because total volatility and idiosyncratic volatility are very highly correlated (normally greater than 95%), it is not surprising that we find similar results regardless of whether we choose to focus our testing on idiosyncratic volatility or total volatility.[3]

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:

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

[3] The results for total volatility are available upon request.

Where, $R_{M,t} - R_{f,t}$, SMB, and HML constitute the Fama-French market, size and value factors, respectively. We use the daily stock and factor returns in the prior month to estimate IVOL for month *t*. We correlate the idiosyncratic risk from the current month with the subsequent monthly returns (inclusive of dividends).

Tests and Results

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 based factor and the level of IVOL while controlling for the well known size and style effects. Size is measured as the logarithm of the equity market capitalization obtained at the end of the prior month, and book-to-market is measured as the logarithm of one plus the book-to-market ratio of equity. We use accounting data for the prior fiscal year.

When estimated, our model will load most heavily on those risk factors potentially responsible for the return predicting powers of the IVOL characteristic (if risk is indeed the driver). This procedure extracts risk factors even if the researcher does not directly observe the factor structure underlying stock returns. To elaborate, we follow Fama and French (1992) and Daniel and Titman (1997) by constructing zero-investment factor mimicking portfolios for IVOL. We create these portfolios by sorting stocks independently into NYSE size terciles and terciles based on the IVOL characteristic across all stocks at the end of each month. We obtain a total of nine value-weighted portfolios for the IVOL characteristic: 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 three IVOL portfolios that are size independent. In order to calculate the zero-cost return portfolios representing the IVOL-based factors, we difference the extreme portfolios as sorted on the IVOL characteristic.

Following Fama and French (1992), we estimate factor loadings at the portfolio level and then assign the portfolio loadings to individual stocks within the portfolio in the firm-level Fama-MacBeth (1973) cross sectional regressions. Specifically, at the end of each month *t*, all stocks on the NYSE, AMEX and Nasdaq are independently sorted into four size groups based on the size breakpoints for all NYSE stocks. Four groups are also created as sorted on the IVOL characteristic and another four groups are created as sorted on the firm-level loadings on the IVOL factor, all based on the breakpoints for all stocks.

To obtain the pre-sorting firm-level factor loadings, we conduct rolling regressions of the monthly excess returns of each firm over the last 36 months (24 months minimum) on both the Fama-French (1993) three factors plus the IVOL-based factor for each month. We obtain the value-weighted monthly returns on these 64 size/IVOL characteristic/IVOL factor loadings portfolios for the month $t+1$. For each month, we obtain the portfolio factor loadings with 36 month rolling regressions of contemporaneous monthly excess returns of each portfolio on the size, book-to-market, and IVOL factors. We then assign to each stock the portfolio factor loadings of the size/IVOL-characteristic/IVOL-factor-loading group that it belongs to at the end of the prior month. This procedure potentially mitigates the estimation errors related to noise from the factor loadings of individual stocks while allowing more precise estimates of firm level characteristics.

Table 1 presents the results. Column (1) shows that the loading on the IVOL-based factor is insignificantly related to subsequent stock returns when measured alone (t = 0.16). By contrast, Column (2) shows that the IVOL characteristic can alone predict subsequent stock returns at the 1% level of significance. Columns (3), (4), and (5) present the results with the inclusion of other control variables to include the IVOL factor loadings and IVOL characteristics. For all regressions we find a statistically insignificant loading on the IVOL-based factor, whereas the IVOL characteristic is always highly significant at the 1% level. The results from our cross sectional regressions indicate that average subsequent returns are determined by common variation associated with the IVOL characteristic rather than factor loadings. This analysis strongly suggests that the return predictive power associated with IVOL is best explained by a market mispricing rather than some pervasive risk factor.

Double Sorting on Both Characteristics and Factor Loadings

In this section, we form "characteristic-balanced" portfolios in order to test whether the (high and low) 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, we double sort individual stocks into quintile portfolios based separately on the IVOL characteristic and the loadings on the IVOL-based factors. As noted by Daniel and Titman (1997), 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 risks. This is so because the characteristic and the constructed factor tend to positively correlate. Should the IVOL factor loadings explain the cross-section variation of stock returns in these double sorts 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 risks. 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.

Before conducting the formal test with "characteristic-balanced" loading-based quintile spread portfolios within the IVOL characteristic quintiles, we first conduct a rank portfolio test in order to separately explore 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. Specifically, we equally assign firms to quintile portfolios according to the magnitude of their prior month's IVOL characteristic and IVOL-based factor loadings. We then calculate the following month's equal-weighted return for each quintile portfolio. We then separately measure the return predicting power for the IVOL characteristic and the IVOL-based factor loadings, calculated as the abnormal returns on the quintile spread portfolio, or the difference portfolio between the lowest- and highest-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.[4]

Table 2 shows that sorting solely on the IVOL-based factor loadings generates insignificant differences in returns across the factor loading quintile portfolios; the difference portfolio demonstrates an insignificant coefficient estimate of -0.09 (t = -0.67). In comparison, sorting solely on the IVOL characteristic generates significant differences in returns across the factor loading quintile portfolios. The IVOL characteristic spread portfolio has a significant coefficient estimate of 1.04 (t =2.81). From the coefficient estimate of the difference portfolios, adjusted for the Fama-French

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

(1993) three-factors, we calculate the implied annualized abnormal monthly return as 13.22% (= $(1 + 1.04\%)^{12} - 1$).

We now conduct the formal test using "characteristic-balanced" loading-based quintile spread portfolios within the IVOL characteristic quintiles. To accomplish this, we obtain equal-weighted returns for the 25 portfolios created through independent quintile sorts on the IVOL characteristic *and* the loadings on the IVOL-based factor. Table 3 reports the regression intercepts resulting from time series regressions of the excess returns of the 25 portfolios on the Fama-French (1993) three factors.

Our results show that even when controlling for factor loadings, the IVOL characteristic remains significantly related to subsequent stock returns. The quintile spread portfolios created from the IVOL characteristic yield highly significant results for every one of the quintiles based on the IVOL-based factor loadings. Four of the five quintile spread portfolios based on the IVOL characteristic have abnormal returns significant at the 1% level, whereas the fifth quintile spread portfolio shows 5% abnormal return significance. In contrast, when controlling for the IVOL characteristic, the IVOL-based factor loadings present no significant explanatory power for any of the quintile spreads in the cross-section of subsequent stock returns. That is, none of the quintile spreads based on the loadings on the IVOL-based factors appear significant. These results again point us towards rejecting the explanation that abnormal returns associated with IVOL derive from systematic risks in favor of the explanation that the likely return source emanates from some sort of market mispricing.

To summarize, researchers have identified prior stock return 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 volatility stocks do not arise because of the correlations of these stocks with pervasive (systematic) factors. Instead, our results indicate that the abnormal returns on low volatility stocks arise from some market mispricing associated with certain characteristics present in low volatility firms.

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 IVOL portfolios identified in prior literature cannot be viewed as compensation for factor risk.

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Table 1
Monthly Fama-MacBeth (1973) Regressions of Stock Returns on the IVOL Characteristic and IVOL-based Factor

Table 1 reports the results of the Fama-MacBeth (1973) regressions whose dependent variables are the monthly returns of individual stocks for the 12 months following the portfolio formation month. The reported coefficient estimates are the time-series means of the estimated parameters from the monthly cross-sectional regressions (in percentage), described below. Stock returns are adjusted for dividends, delisted returns are from CRSP, and accounting variable data are from Compustat. Robust Newey-West (1987) t-statistics are in parentheses.

We assign to each stock the loading on the IVOL-based factor associated with the 64 size / IVOL-characteristic / IVOL-factor portfolio it belongs to. We calculate the portfolio-level factor loadings for IVOL as follows: at the end of each month *t*, all stocks on NYSE, AMEX and Nasdaq are assigned to one of four size groups (with breakpoints based on all NYSE firms), and one of four groups based on the IVOL characteristic, and one of four groups based on the firm-level pre-sorting loadings of the IVOL-based factors (with breakpoints based on all firms).

We then obtain value-weighted monthly returns for each of the resulting 64 portfolios. For each month, we next obtain the portfolio factor loadings using 36 month rolling regressions of contemporaneous monthly excess returns for each portfolio on $r_m - r_f$, *SMB*, *HML*, and the IVOL-based factor. To obtain the pre-sorted firm-level monthly factor loadings used to create the 64 portfolios, we estimate rolling regressions of the monthly excess returns of each firm over the last 36 months (24 months minimum) on $r_m - r_f$, *SMB*, *HML*, and the IVOL-based factor.

To obtain the IVOL-based factor, we produce nine portfolios, one for each combination of the three IVOL characteristic portfolios and the three size portfolios as of the end of month *t*. We then equally weigh each IVOL portfolio across the size terciles to obtain three IVOL portfolios that are size independent. To calculate the zero-cost return portfolios representing the IVOL-based factors, we difference the extreme portfolios as sorted on the IVOL characteristic. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The data are from 1962 through 2008.

Variable	(1)	(2)	(3)	(4)	(5)
IVOL Factor	0.08		0.07		-0.18
	(0.16)		(0.14)		(-0.41)
IVOL Characteristic		-1.23***		-1.22 ***	-1.13 ***
		(-2.71)		(-2.68)	(-2.61)
Market Capitalization			0.06	0.01	-0.03
			(055)	(0.17)	(-0.37)
Market-to-Book			-0.71 ***	-0.58 ***	-0.70 ***
			(-4.79)	(-4.56)	(-5.06)
Intercept	1.13 ***	1.74***	1.13 ***	1.75***	1.81***
	(2.81)	(11.82)	(2.79)	(11.74)	(6.73)

Table 2
Monthly Fama-French (1993) Factor-Adjusted Returns of Quintile Portfolios

Table 2 reports the coefficient estimates for the intercept of the Fama-French (1993) three-factor model in percentage. The dependent variables are the monthly excess returns of equal-weighted quintile portfolios formed annually by assigning firms into quintiles based on the magnitude of the prior month's IVOL characteristic and IVOL factor loadings. Stock returns adjusted for dividends and delisting returns are from CRSP and accounting variables are from Compustat. 1 (5) corresponds to the quintile firms with the lowest (highest) IVOL characteristic. 1-5 is the difference portfolio between the lowest- and highest-ranked quintile, or quintile spread, portfolios. 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 1962 through 2008.

Rank	IVOL Characteristic	IVOL Factor Loading
1	1.38 ***	1.11 ***
	(10.25)	(3.69)
2	1.40 ***	1.13 ***
	(7.21)	(4.32)
3	1.37 ***	1.23 ***
	(5.47)	(4.97)
4	1.17 ***	1.18 ***
	(3.60)	(4.85)
5	0.34	1.20 ***
	(0.78)	(4.58)
1-5	1.04 ***	-0.09
	(2.81)	(-0.67)

Table 3
Factor-Adjusted Portfolio Returns from Independent Sorts on the IVOL Characteristics and the IVOL-Based Factor Loadings

Table 3 reports the intercept in percentage of time series regressions whose dependent variables are the equal-weighted monthly returns of 25 portfolios. The independent variables are the Fama-French (1993) three factors plus the IVOL-based factor. We independently sort all stocks into quintiles based on the IVOL characteristic and the loadings on the IVOL-based factor of individual firms separately using breakpoints for all firms. We estimate the individual firm-level pre-sorting loadings on the IVOL-based factors with a rolling regression of the monthly excess returns of each firm over the last 36 months (24 months minimum) on $r_m - r_f$, *SMB*, *HML*, and the IVOL-based factor. For each month, we also take the difference in portfolio return for the extreme quintiles.

To obtain the IVOL-based factor, we first sort stocks independently by the IVOL characteristic among all stocks and NYSE-size terciles each month. This produces nine portfolios. We then equally weigh each of the IVOL portfolios across the size terciles, to obtain three IVOL portfolios that are size independent. Portfolios are resorted every month. We difference the extreme portfolios sorted on the IVOL characteristic in order to calculate the zero-cost portfolio returns as the IVOL-based factor. 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 1962 through 2008.

		Characteristic Portfolio					
		1	2	3	4	5	1-5
Factor Loading Portfolio	1	0.86 ***	0.92 ***	0.87 ***	0.77 **	-0.02	0.87 **
		(5.20)	(4.20)	(3.04)	(2.01)	(-0.03)	(2.04)
	2	1.00 ***	0.86 ***	0.76 ***	0.52	0.02	0.98 ***
		(6.44)	(4.04)	(2.80)	(1.52)	(0.04)	(2.41)
	3	1.02 ***	0.96 ***	0.88 ***	0.63 *	-0.11	1.13 ***
		(6.76)	(4.59)	(3.33)	(1.84)	(-0.23)	(2.81)
	4	0.94 ***	0.88 ***	0.83 ***	0.65 **	-0.05	0.99 ***
		(6.50)	(4.24)	(3.13)	(1.97)	(-0.12)	(2.54)
	5	0.98 ***	0.85 ***	0.92 ***	0.91 ***	-0.21	1.19 ***
		(6.45)	(3.99)	(3.34)	(2.57)	(-0.44)	(2.98)
	1-5	-0.13	0.06	-0.05	-0.13	0.19	
		(-1.24)	(0.56)	(-0.34)	(-0.69)	(0.70)	