Predicting Extreme Returns and Portfolio Management Implications

Krieger, Kevin and Fodor, Andy and Mauck, Nathan and Stevenson, Greg

14 May 2012

Predicting Extreme Returns and Portfolio Management Implications

Abstract

We consider which readily observable characteristics of individual stocks (e.g., option implied volatility, accounting data, analyst data) may be used to forecast subsequent extreme price movements. We are the first to explicitly consider the predictive influence of option implied volatility in such a framework, which we unsurprisingly find to be an important indicator of future extreme price movements. However, after controlling for implied volatility levels, other factors, particularly firm age and size, still have additional predictive power of extreme future returns. Furthermore, excluding predicted extreme return stocks leads to a portfolio that has lower risk (standard deviation of returns) without sacrificing performance.

1. Introduction

Traditional studies often seek out firm characteristics or tendencies that may be linked to higher expected returns. While such studies are numerous, and many other works examine the forecasting of future variance levels, markedly less research investigates the question of whether firms experiencing returns of high magnitude (positive or negative) may be identifiable ex ante. We consider whether firms exhibiting extreme returns have common characteristics. If so, can extreme return firms of future periods be predicted? Furthermore, can portfolio variances be reduced by eliminating firms likely to have extreme future returns without adversely affecting portfolio performance?

Ang, Hodrick, Xing, and Zhang (2006, 2009) examine the pricing of idiosyncratic risk in the cross-section. They find that portfolios consisting of firms with the highest idiosyncratic risk are characterized by negative alphas and significantly underperform a portfolio of stocks with the lowest idiosyncratic risk. Blitz and Van Vilet (2007) study the possibility of actively managing portfolios to benefit from the inclusion of low volatility stocks. Using U.S., European, and Japanese stocks they document a 12% spread between low and high volatility portfolios and argue that, in practice, portfolio managers should add low volatility stocks as a separate asset class. Although the advantages of low volatility firms have been documented, many portfolio managers still overweight high volatility stocks.

We invoke a new approach in this paper. Rather than attempting to pick "winners" we seek to identify extreme return firms ex ante and remove them from a value-weighted market position similar to that held by many passive investors. The ability to identify firms more apt to experience extreme future returns could provide lower risk portfolios.

Stock volatility level serves as perhaps the most intuitive firm characteristic that may aid in the predictability of extreme stock returns. Poon and Granger (1993) outline numerous publications on the methods by which volatility can be forecasted. They demonstrate that the majority of research on predicting volatility favors a stock's implied volatility from option prices, unsurprising given that implied volatility reflects active perceptions of future levels of volatility.

Information available in companies' financial statements may also indicate extreme future equity returns. Accounting variables, fundamental analysis, and trading characteristics help predict returns in past research on firm size and book-to-market ratios (Fama and French, 2002), trading volume (Campbell, Grossman and Wang, 1993), price momentum (Jegadeesh and Titman, 1993), dividend yields (Hodrick, 1992), accruals (Sloan, 1996) and earnings predictions (Lev and Thiagarajan, 1993). We consider the impact of such measures on the likelihood that firms will exhibit extreme future price movements.

Reinganum (1988) and Beneish, Lee and Tarpley (2001) use unique, directionally-oriented approaches that consider market-based signals in order to identify potential extreme price movements. Among this group of 12 market-based signals, Beneish, Lee and Tarpley (2001) find that relatively younger firms with lower market capitalization, lower stock prices, higher trading volume, lower sales-to-price ratios, lower analyst coverage, and higher return volatility are more likely to exhibit large movements. The authors, however, do not consider the potential impact of implied volatility as a predictive measure. Also, whereas Beneish, Lee and Tarpley (2001) utilize their prediction scheme as the first stage of a two-stage process seeking out profitable firms, we attempt to decrease portfolio variance by eliminating firms likely to experience large price movements.

Dong, Duan and Jang (2003) propose a different application of the variables presented by Beneish, Lee and Tarpley (2001), as well as a neural network model that decreases necessary variables, and thus increases sample size. This process reveals that only a subset of the explanatory variables used by Beneish, Lee and Tarpley (2001), namely market capitalization, price, age, and the presence of a recent loss in income or decline in sales, are useful. Again, however, implied volatility is not utilized. Dong, Duan and Jang (2003) find that smaller firms, firms with lower stock prices, and younger firms are more likely to experience extreme price movements. As an additional measure, we also consider analyst forecast dispersion as a potential predictor of extreme returns. Differences of opinion regarding future firm performance might indicate a wider range of potential prices that a stock may reach in a given period.

In this paper, we utilize a probit regression framework in hopes of identifying the characteristics of firms with extreme future price movements. Implied volatility from options, a new consideration in this line of research, strongly predicts future extreme price movements. It is highly significant in a Fama-Macbeth framework and enters every annual probit regression, regardless of selection criteria. Implied volatility adds greatly to our successful identification frequency of future extreme return firms. Given that implied volatility arises from market prices, one possibility is that all predictability of extreme future returns may be captured by these volatility levels. However, we further find firm size and age frequently have additional explanatory power. Younger and smaller firms are more likely to experience extreme future returns, even when the implied volatility predictor is also included.

Utilizing an ex ante approach to identify firms with extreme price movements significantly improves the success of identification above random levels. When we remove predicted extreme price movers from a widespread portfolio, the day-to-day variation of the portfolio declines significantly over the study period while the overall returns of the portfolio do not suffer. In fact, when we delete predicted extreme return stocks from a position which otherwise mimics the value-weighted equity market, performance over the past 15 years actually improves.

2. Data and Methodology

Our sample period is 1996 through 2010. We collect implied volatility data from Optionmetrics.[1] Christensen and Prabhala (1998) and Li (2002) describe the usefulness of at-the-money options, and those near maturity, due to the strong liquidity of such options. With strong liquidity, fewer possibilities for mispricing exist, and such options also more fully reflect market expectations for short-term volatility. The results presented in this paper are based on the implied volatilities of available call options nearest at-the-money status expiring mid-February of the following year (approximately seven weeks after positions are formed since liquidity for such options is relatively high). We collect equity returns from CRSP, and this data is used to identify "extreme" (high magnitude) returns in

[1] Results are robust to the choice of option maturity, moneyness and type (put implied volatility yields results similar to calls).

the following year[2], including bankruptcy or bankruptcy-like delistings from equity exchanges. We identify delisted firms via CRSP delisting codes. As in Dichev (1998) and Brockman and Turtle (2003), CRSP codes 400 and 550-585 are classified as bankruptcy-type delistings. We gather trading volume (shares traded in the past year), current stock price, and market capitalization data from CRSP. We exclude firms with stock prices below $5, as well as firms that do not trade on the NYSE, NASDAQ or AMEX. We utilize the natural log of firm age (in months), price, volume (in millions of shares) and size (in millions of dollars) for extreme return prediction as we posit the marginal impacts of these variables are likely to decrease as their values increase. We calculate firm age, in months, based on the initial appearance month in CRSP. For firms appearing in CRSP prior to January 1962, we record January of 1962 as the initial month. We expect smaller, lower price, and younger firms will be more likely to experience extreme future returns. However, in a regression framework, we note that no additional explanatory power may be added if implied volatility is an all-encompassing metric describing future stock behavior.

We gather analyst forecast data from IBES. We calculate forecast dispersion, based on the most recently available data on December 31st of each year, as the standard deviation of initial earnings estimates for the most recent quarter. We expect those firms with higher forecast dispersion to experience more extreme future returns as a greater level of uncertainty exists regarding their prospects.[3] We gather book value of equity from Compustat in order to construct the book-to-market ratio. We also take research and

[2] Alternatively, we considered one-month and six-month return horizons and found similar links to the predictor variables discussed.

[3] The difficulty of effectively shorting stocks has dropped over time, particularly given the introduction of Single Stock Futures (SSFs) in 2002, midway through our sample period. Thus, the motivation for Miller's (1977) conjecture that forecast dispersion may be indicative of overvalued stocks may be less relevant moving forward. The use of forecast dispersion to predict non-directional *extreme* movement seems, to us, perhaps more relevant moving forward.

development data from Compustat, as firms making greater efforts to develop new technology or techniques may be prone to greater swings in firm value. We utilize the most recently available Compustat data as of each December 31st, and we compute the book to market value ratio based on the market value from those dates.

We require observations to have data for all variables (with the exception of R&D expenditures for which missing values are set to 0), major exchange status, and share price greater than $5, and this results in a sample of large, established firms relative to the universe of all CRSP observations. Requiring implied volatility data and a minimum of two analysts following the firm in IBES further limits the sample considerably. Our final annual samples range in size from 1,100 to 1,600 firms per year. We clearly acknowledged that when we refer to the explanatory power of "age" and "size", and when we note that "younger" and "smaller" firms are more likely to exhibit extreme returns, these findings are determined *after* mandating the inclusion of implied volatility and forecast dispersion as explanatory measures.

At first, this may seem troubling, but while our sample restrictions result in a wide deletion of firms, the market capitalization of our remaining sample represents over 85% of the CRSP database total market capitalization each sample year (and over 90% in the majority of years). The small sizes of the omitted firms imply that their deletion results in only a small impact on the value-weighted portfolio returns we examine. We seek to improve upon the performance of a typical, value-weighted, market mimicking portfolio by deleting a few firms which have a high likelihood of exhibiting an extreme return in the following year, and our final sample allows us to consider this question genuinely.

We consider the power of a number of explanatory variables to predict the likelihood of a firm experiencing extreme returns over the next year. We perform probit regressions for the occurrence of extreme price changes over the next calendar year based on explanatory variables observed on the final trading day of the preceding year or over the course of the preceding year. To determine our regression coefficients from the probit, we classify firms which prove to be in the highest 3% or lowest 2.5% of realized returns in the following year as having extreme returns. Additionally, we classify firms which delist from the CRSP database due to bankruptcy or bankruptcy-type reasons in the following year as having extreme returns. Given that roughly 0.5% of firms (meeting our data requirements) are delisted per year, on average, for failure-type reasons, we choose the 3% upper threshold and the 2.5% lower threshold of returns to give relatively equal numbers of high and low extreme movers each year. Results are robust to various threshold levels for extreme returns (for example, the highest and lowest 2% of returns and bankruptcy delistings, or the highest 2% and lowest 1.5% of returns and bankruptcy delistings, etc.).

We employ these classifications, along with the previously presented explanatory variables, to estimate the probit regression specification:

$$Pr(I_j) = \Phi(\alpha + \beta_1(BM) + \beta_2(Disp) + \beta_3(IV) + \beta_4(Size) + \beta_5(Age) + \beta_6(Vol) + \beta_7(RD) + \beta_8(Price)) + \varepsilon_j \qquad (1)$$

Where Pr is the probability the indicator variable $I_j = 1$ (indicating an extreme return observation) and $\Phi(*)$ is the cumulative normal distribution function. Equation 1 is estimated on an annual basis. *BM* is the book-to-market ratio formed based on the available data on December 31st of each year, *Disp* is the analyst forecast dispersion on this date, *IV* is the implied volatility of the call option closest to at-the-money status which expires in February of the following year, *Size* is the natural log of market capitalization (in millions of dollars), *Age* is natural log of firm age in months, *Vol* is the natural log of the trading volume, i.e., the average number of shares traded daily over the previous year (in millions), *RD* is the research and development expense of firms in the previous year based on the most recently available data on December 31st of each year, *Price* is the natural log of firm price, and ε_j is the error term.[4]

We calculate Fama-Macbeth coefficients using annual probit regression coefficients, and Newey-West standard errors of these annual coefficients are used to calculate t-statistics. We also estimate probit coefficients on an annual basis utilizing both backward and stepwise selection criteria to determine the robustness of the utility of various predictors.

We must take care to employ a fully ex ante approach in order to predict extreme returns. We conduct all regressions based on predictors observable on December 31st of a year and the equity returns of the subsequent year. We estimate coefficients from a given year and use these coefficients, along with the new data for each predictor variable, to predict extreme return status in the following year.[5] Using this method, there are no look-ahead biases in our portfolio construction; each rebalance is possible via information readily available to fund managers every December 31st. For example, we conduct a probit

[4] Additional explanatory variables, such as number of analysts following the firm and the sales loss indicator of Beneish, Lee, and Tarpley (2001) were considered but held little additional explanatory power. Only potential predictors which entered the backward or stepwise regression specifications for at least two of the 14 annual specifications were kept for purposes of presentation. We also consider industry effects, but they have little predictive power.

[5] The performance of portfolios which are rebalanced on a more frequent or less frequent basis may serve as an exercise for future research.

regression linking the probability of extreme returns in 1998 to end-of-1997 explanatory variables. We then use these coefficients, along with explanatory variables observable on December 31st, 1998, to predict which firms will have extreme returns for the year 1999. We designate the firms with the highest 6% of extreme return probabilities as "predicted extreme" firms. We then track these firms to determine the effectiveness of our predictive methodology.[6] We present two statistics. First, we present the "recognized" percentage, which is based on the number of extreme movement firms that were correctly predicted, ex ante. Second, we present the "realized" percentage, which is calculated based on the number of predicted extreme movement firms which indeed exhibit extreme price movements. These percentages are typically similar; however, the variation in the number of bankruptcy delisting firms from year to year results in some divergence. We also compare the performance and variability of annual, value-weighted portfolios which do and do not include predicted extreme movement firms. While earlier works considere how low risk portfolios may improve the value of investors, ours is the first paper, of which we are aware, designed to improve portfolio performance by predicting extreme magnitude stocks ex ante and adjusting holdings accordingly.

3. Results

[6] We must, of course, make the classifications of whether or not firms are "predicted extreme" ex ante. Future one-year returns data are unavailable for a few firms. If the reason for unavailability is a delisting due to bankruptcy or bankruptcy-like reasons, as denoted by CRSP, then we classify the firm, ex post, as an "actual" extreme movement firm. If, however, a firm cannot be accurately traced for the following year for other reasons, we omit the observation from the sample (for both predicted extreme and non-extreme firms). While 6% of firms are predicted to be extreme movement firms, ex ante, these omissions result in the final sample of firms having a "predicted extreme" ratio slightly different than 6%.

Table 1 presents descriptive statistics after dividing the sample based on whether extreme returns were experienced by firms in the following year. Firms in the highest 3% or lowest 2.5% of equity returns, or delisting for bankruptcy or bankruptcy-like reasons, are considered extreme return firms.

(Insert Table 1)

As expected, and consistent with prior literature, extreme return firms are smaller size firms, younger firms, and have lower stock prices. For all these variables, mean and median differences between extreme and non-extreme return firms are significant at the 1% level. Mean and median implied volatility and analyst forecast dispersion are larger for extreme return firms relative to non-extreme returns. These differences are also in the predicted direction, and significant at the 1% (5%) level for implied volatility (forecast dispersion). Trading volume is lower for extreme return firms, but the difference is only marginally significant. Research and development costs are higher for non-extreme return firms. Differences for both means and medians are significant at the 1% level. At first, these findings seem contrary to our intuition, but volume and R&D costs are thus far unadjusted for firm size. It is important to test the power of all variables to predict extreme returns in a multivariate framework as correlations between many variables are significant. We accomplish this through the use of probit analysis.

Table 2 presents Fama-Macbeth probit coefficients. The coefficients of implied volatility, age, and size are significant at the 1% level. The signs of these variables are as expected. Younger firms, smaller firms and firms with higher implied volatilities are more likely to experience extreme price movements in the following year. The coefficient for volume is now positive and marginally significant, consistent with prior literature. After inclusion of size in the regression framework, the coefficient for R&D costs is insignificant, contrary to the implications of Table 1.

(Insert Table 2)

Also, in Table 2, we present the results of backward and stepwise selection procedures. We report the percentage of annual probit models for which each explanatory variable enters (for stepwise selection) or remains (for backward selection). We find implied volatility is useful as a predictor of extreme returns in each year, while age and firm size are each useful in roughly half of the annual specifications. This is true for both the backward and stepwise procedures. Price was also significant in a number of annual regressions; however, the sign of the significant price coefficient was not always consistent with Fama-Macbeth results (unlike for the age and size predictors).

Table 3 presents prediction accuracy results. On the last day of each year we use the regression coefficients, estimated from the previous year's probit regression, along with the values of each predictor available on that day, to predict which firms will exhibit extreme returns in the following year.[7] We identify firms in the highest 6% of probit estimates as "predicted extreme return" firms. We classify the percentage of actual extreme return firms correctly found in the "predicted" sample in the given year as "recognized". We classify the percentage of predicted extreme return firms confirmed to

[7] Alternatively, the average of the coefficients estimated by the probit models to explain extreme return status in the prior three years was considered. Results were similar.

actually *be* extreme return firms as “realized”. For example, in 2008, of the 92 firms that were in the top 3% or bottom 2.5% of returns, or delisted for bankruptcy or bankruptcy-like reasons, 12 were predicted to be extreme movers. This results in a 13.04% “recognized” level. Of the 80 firms (remaining after data-driven omissions) predicted to be in the extreme return sample, those 12 firms were confirmed to be extreme return firms. This results in a 15.00% “realized” level.

(Insert Table 3)

To illustrate the relevance of the findings of Table 3, suppose that 1,000 stocks were analyzed in a given year. Of these, if 6% were picked at random this would be 60 stocks. Of this random sample, we would expect to find 6%, or 3.6, to be correctly predicted as extreme movement firms by random chance. The random “recognized” and “realized” statistics would each be 6%. As can be seen in Table 3, the “realized” and “recognized” percentage levels are notably higher than 6% in each year’s observations. In actuality, we reject a chi-square test for independence, each year, at the 1% level, with the exception of 1997.

Improved ex ante identification of extreme movement firms may provide portfolio management benefits. Low risk portfolios have garnered increased attention in recent literature due to benefits provided for investors, and the question remains what improvements may arise from our approach. Table 4 shows the performance of annual portfolios that include all sample firms as well as the performance of portfolios which exclude predicted extreme return firms. The annual return of each portfolio is presented, as is the annualized standard deviation of the daily returns of each portfolio.

(Insert Table 4)

The daily standard deviation of returns for the entire period is significantly smaller, at the 1% level, than the daily standard deviation of returns for the full sample. For the entire sample period, the portfolio that excludes predicted extreme movement firms has a 5.70% annual geometric mean with an annualized standard deviation of 24.63%, while the portfolio that includes all sample firms has an annual geometric mean of 4.99% with an annualized standard deviation of 26.08%. Along with the reported superior returns for the "no extreme" sample for the full sample period, we note that in 11 of 14 years, the portfolio which excludes predicted extreme movement firms exhibits both lower day-to-day variation and a superior return. Thus, it does not appear that the lower variation from an approach deleting predicted extreme movement firms comes as a result of sacrificing superior returns.[8] The approach also does not result in inferior returns in times of market distress. The four sample years with the poorest market returns: 2000, 2001, 2002 and

[8] As an alternative to the portfolios discussed herein, we consider the performance of an equally weighted full sample portfolio. When predicted extreme firms are weighted at their value levels (which shrinks the weights of most predicted extreme firms) and other stocks are then equally weighted, conclusions similar to the value-weighted case arise. The return levels of the full sample, equally weighted portfolio and the sample which first value weights predicted extreme firms are similar; however, the variation of the latter portfolio is significantly reduced, both annually and over the full sample period.

2008 actually saw superior returns (along with the customary reduced daily variation) for the portfolio which omits predicted extreme movement firms.[9]

4. Superiority over One-Sided Predictions

Given the demonstrated ability to predict firms likely to have extreme returns in the following year and the risk reduction benefits of excluding these firms, we next attempt to identify firms likely to have positive extreme returns and negative extreme returns separately. If we can frequently successfully identify firms likely to have extreme negative returns, it would be more sensible to exclude only these firms from a portfolio[10], or we may choose to invest only in firms predicted to have large positive price movements.

(Insert Table 5)

In Table 5 we report Fama-Macbeth probit results separately for predictions of large positive and large negative return firms. We consider those in the highest 6% of returns for the year to be "extreme positive return firms" and firms in the lowest 5.5% of equity returns or delisting for bankruptcy or bankruptcy-like reasons to be "extreme negative return firms". For the positive model, coefficients of implied volatility, firm age, and

---

[9] Finally, we note that the market capitalization of the excluded firms represents, on average, 2.3% of the overall market capitalization of our sample. For the minimum (maximum) year, this figure is 0.9% (3.4%). The predicted extreme return portfolio has a CAPM beta of 1.30, based on monthly market returns over the full sample period.

[10] This assumes that firms with predicted extreme negative movement are not low (or even negative) beta firms, which could thus offer diversification benefits to investors. In our sample, this assumption is valid.

forecast dispersion are significant at the 1%, 5%, and 5% levels, respectively. Younger firms and firms with higher option implied volatilities are more likely to experience extreme positive outcomes in the future year, consistent with our earlier results. Firms with lower forecast dispersion experience extreme positive returns in the following year more frequently. Smaller firms are also more likely, at the 5% significance level, to realize extreme positive returns in the following year.

For the negative model, we find coefficients of implied volatility and age to be significant at the 1% level and the size coefficient to be significant at the 5% level. Younger firms, smaller firms, and those firms with higher option implied volatilities experience extreme negative future outcomes more frequently. In general, these results support those from the model predicting all extreme returns firms, presented in Table 2.

We next test the ability of these models to correctly identify extreme positive and negative return firms. We present these results in Table 6. As in the Table 3 analysis, at the beginning of each year we use the regression coefficients for the positive and negative extreme return models, estimated via the previous year's probit regressions, to predict which firms will exhibit extreme positive or negative returns in the following year. We classify the percentage of extreme return firms correctly predicted in the given year as "recognized". We classify the percentage of predicted extreme return firms confirmed to be extreme return firms as "realized". We identify the top 6% of firms from each specification as predicted positive (negative) extreme returns firms.

(Insert Table 6)

Both models underperform the non-directional model in identifying extreme return firms. The positive extreme return model has recognized and realized percentages of 9.72% and 9.79%, respectively, compared to 15.71% and 16.76% for the non-directional model. The negative extreme return model has recognized and realized percentages of 9.62% and 9.48%, respectively. The two-sided approach greatly outperforms the one-sided approach. We posit that the modeling approach we utilize performs well in forecasting the second moment of returns but is not particularly successful at forecasting the first moment.[11] Hence, the primary improvement to portfolio selection from our approach comes about through decreased variation.

To briefly demonstrate the importance of implied volatility in predicting extreme returns we also present the overall success of the original, non-directional model when implied volatility is excluded as a potential predictor. Recognized and realized percentages decrease to 8.84% and 9.43%, respectively, when implied volatility is excluded from the model. We find this decline in model utility to be unsurprising given the extreme significance of the implied volatility variable; however, the significant prediction abilities of other variables (notably, in results not shown, age and size) deter the identification frequencies from declining to random levels.

We also present the annual and overall results for a portfolio which deletes those firms predicted to be in the lowest 5.5% of returns for the following year or to delist due to bankruptcy or bankruptcy-like reasons. If such a portfolio were to offer superior profitability or lower variation, then the approach of omitting *all* predicted extreme

[11] This is somewhat akin to types of modeling done by Barra (a brand of MSCI Inc.), which seeks to explain the second moment of returns with selected predictors.

movement firms would not be optimal.[12] The results, analogous to Table 4, are shown in Table 7.

(Insert Table 7)

The annual geometric mean return of the approach deleting only predicted extreme negative firms is slightly higher than that of the approach deleting all predicted extreme movement firms, but this improvement is by only 18 basis points (5.88% for the 1997-2010 period, vs. 5.70%, as seen in Table 4). More strikingly, the one-sided approach severely compromises the reduction in variation seen in Table 4. The drop in annualized daily standard deviation shrinks to only 0.50%, as opposed to the significant decline of 1.45% noted in Table 4. Only 10 of 14 individual years have drops in variation under the approach which removes only predicted extreme negative firms (as opposed to all 14 years in Table 4), and only 4 of these drops are statistically significant at the 5% level (as opposed to 11 in Table 4).

It appears that an approach which attempts to eliminate all extreme movement firms, in order to reduce portfolio variation, outperforms an approach which seeks superior returns, along with reduced variation, by excluding only predicted extreme negative movers. Moreover, while the portfolio which eliminates only predicted extreme negative firms demonstrates a slightly higher return than the dual-direction approach, most investors will not view this increase as enough to compensate for the much smaller improvement in terms of variation.

---

[12] A portfolio including only predicted extreme positive movement firms has a marginally improved return but an unsurprisingly high daily standard deviation.

5. Conclusion

We seek to contribute to the literature analyzing stock returns through a unique approach: examining the predictability of extreme returns. We consider a combination of implied volatility, accounting data, and analyst forecast data in order to identify firms that are more likely to have extreme future returns. When we exclude firms predicted to have extreme future price changes, day-to-day portfolio variation is significantly lowered without sacrificing return levels. In all but two years of our 14 year study, the portfolio that excludes stocks predicted to have extreme movements has significantly lower day-to-day variation with improved returns. This finding also applies to the overall 14-year period. Attempts to identify positive or negative extreme return firms separately do not result in improvements as notable as those predicted by the non-directional model.

We find a firm's implied volatility, size, and age have power to predict future extreme price movements. As hypothesized, implied volatility is positively related to the probability of extreme price movements while size and age are negatively related. Implied volatility is the most consistent and powerful predictor of future extreme price movements, but its information may be supplemented by additional considerations. The most relevant prior study in this area is that of Beneish, Lee and Tarpley (2001) who determine that extreme movement firms can be somewhat identified, ex ante. Their study, however, focuses on the distinction between the characteristics of predicting returns for those firms which are extreme performers and those which are not. Like Beneish, Lee, and Tarpley (2001), we consider firm size and age to be potentially relevant predictors of a firm having extreme returns. However, our inclusion of implied volatility, the most important measure in the prediction framework, is a new contribution to the literature. This measure changes the predictability of extreme returns considerably.

Rather than picking winners, we focus on lowering portfolio variation by removing potentially extreme moving firms from holdings. We report considerable, statistically significant success based on our two-sided approach. One-sided approaches do not provide the same degree of predictability of extreme returns.

References

Ang, A., R.J. Hodrick, Y. Xing, X. Zhang, 2006. The cross-section of volatility and expected returns, Journal of Finance 61, 259-299.

Ang, A., R.J. Hodrick, Y. Xing, X. Zhang, 2009. High idiosyncratic volatility and low returns: International and further U.S. evidence, Journal of Financial Economics 91, 1-23.

Beneish, M. D., C.M.C. Lee, R.L. Tarpley. 2001. Contextual fundamental analysis in the prediction of extreme returns, Review of Accounting Studies 6, 165-189.

Blitz, D., P. Van Vilet, 2007. The volatility effect: Lower risk without lower return, Journal of Portfolio Management 34, 102-113.

Brockman, P. H. J. Turtle, 2003. A barrier option framework for corporate security valuation, Journal of Financial Economics 67, 511-529.

Campbell, J., S. Grossman, J. Wang, 1993. Trading volume and serial correlation in stock returns, The Quarterly Journal of Economics 108, 905–939.

Christensen, B.J., N.R. Prabhala, 1998. The relation between implied and realized volatility, Journal of Financial Economics 50, 125–150.

Dichev, I.D. 2002. Is the risk of bankruptcy a systematic risk?, Journal of Finance 53, 1131-1147.

Dong, I. Duan, C. M.J. Jang, 2003. Predicting extreme stock performance more accurately. Working Paper, Harvard University.

Fama, E. F., French, K. R., 1992. The cross section of expected stock returns, The Journal of Finance 46, 427-466.

Fama, E. F., K. R. French, 1993. Common risk factors in the returns on stocks and Bonds, Journal of Financial Economics 25, 23-49.

Hodrick, R. J., 1992. Dividend Yields and Expected Stock Returns: Alternative Procedures for Inference and Measurement, Review of Financial Studies 5, 357–386.

Jegadeesh, N., S. Titman, 1993. Returns to buying winners and selling losers: implications for stock market efficiency, Journal of Finance 48, 65-91.

Lev, B., S. R. Thiagarajan, 1993. Fundamental information analysis, Journal of Accounting Research 31, 190-215.

Li, K., 2002. Long memory versus option-implied volatility predictions, Journal of Derivatives 9, 9–25.

Miller, E.M., 1977. Risk, uncertainty, and divergence of opinion, The Journal of Finance 32, 1151-1168.

Poon, S.H., C. Granger, 2003. Forecasting volatility in financial markets: a review, Journal of Economic Literature 41, 478–539.

Reinganum, M. R., 1988. The Anatomy of a Stock Market Winner, Financial Analysts Journal March/April, 16–28.

Sloan, R. G., 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings?, The Accounting Review 71, 289-315.

Table 1: Descriptive statistics

This table presents descriptive statistics after dividing the sample according to whether firms experience extreme returns in the following year. Firms in the highest 3% or lowest 2.5% of equity returns, or delisting for bankruptcy or bankruptcy-like reasons, are considered extreme return firms. BM is the book-to-market ratio, Disp is the analyst forecast dispersion, IV is the implied volatility of the call option closest to at-the-money expiring in February of the following year, Size is the log of firm size (in millions of dollars), Age is log of firm age in months, Vol is the log of the average number of shares traded daily in the previous year (in millions), RD is the research and development expense of firms in the previous year in millions of dollars, and Price is the log of firm price. The sample period is from 1997-2010, based on information available the final trading day prior to each new year. For mean differences, significance levels from t-statistics are indicated. For median differences, significance levels from Wilcoxon rank-sum tests are indicated.

	Realized Extreme			Realized Non-Extreme			Difference	
	Mean	Median	Standard Deviation	Mean	Median	Standard Deviation	Mean	Median
BM	0.707	0.655	0.455	0.683	0.623	0.322	0.024	0.032 *
Disp	0.063	0.020	0.422	0.036	0.010	0.125	0.027 **	0.010 **
IV	0.704	0.633	0.344	0.512	0.470	0.266	0.192 ***	0.163 ***
Size	5.888	4.038	1.256	13.590	13.209	1.337	-7.702 ***	-9.171 ***
Age	4.382	4.406	0.963	4.918	4.944	0.885	-0.536 ***	-0.538 ***
Vol	0.288	0.139	0.611	0.335	0.144	0.668	-0.047 *	-0.005
RD	35.220	5.770	45.440	118.77	9.230	58.294	-83.550 ***	-3.460 ***
Price	2.519	2.401	0.882	3.014	2.775	0.718	-0.495 ***	-0.374 ***
	n = 1120			n = 17829				

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2: Fama-Macbeth results and inclusion frequency of predictors

This table presents coefficients and t-stats of the Fama-Macbeth procedure which conducts annual probit regressions of the likelihood of a firm being in the highest 3% or lowest 2.5% of equity returns or delisting for bankruptcy or bankruptcy-like reasons. The sample period covers prediction of extreme returns from 1997 through 2010 with predictor variables measured on the last trading day of the previous year. Additionally, the backward and stepwise selection criteria are utilized to determine which of the regressors enter annual probit regressions. For the 14 years of returns data, the frequency of inclusion for the various predictors in each selection methodology, based on 10% significance thresholds, are listed. BM is the book-to-market ratio, Disp is the analyst forecast dispersion, IV is the implied volatility of the call option closest to at-the-money expiring in February of the following year, Size is the log of firm size (in millions of dollars), Age is log of firm age in months, Vol is the log of the average number of shares traded daily in the previous year (in millions), RD is the research and development expense of firms in the previous year in millions of dollars, and Price is the log of firm price.

	Coefficient	t-value	Backward Inclusion	Stepwise Inclusion
Intercept	-0.282	(-0.55)		
BM	-0.115	(-0.13)	42.9%	42.9%
Disp	0.477	(0.95)	21.4%	21.4%
IV	2.417	(8.84)	100.0%	100.0%
Size	-0.398	(-7.40)	57.1%	50.0%
Age	-0.362	(-4.77)	57.1%	57.1%
Vol	0.133	(1.76)	35.7%	21.4%
RD	-0.003	(-1.38)	14.3%	7.1%
Price	0.091	(0.82)	57.1%	57.1%

Table 3: Predicting extreme returns based on previous year's coefficients

This table presents accuracy results for predicting firms that will have the highest 3% and lowest 2.5% of annual equity returns (or delist for bankruptcy or bankruptcy-like reasons) for the years listed. At the beginning of each year, the probit regression coefficients from the previous year are used to predict which firms will exhibit extreme returns in the following year. The percentage of extreme return firms that were correctly predicted to be so in the given year are classified as "recognized". The percentage of predicted extreme return firms that exhibit extreme price movements are classified as "realized".

1997	Actual No	Actual Yes	1998	Actual No	Actual Yes	1999	Actual No	Actual Yes
Predicted No	978	58	Predicted No	1231	68	Predicted No	1308	74
Predicted Yes	51	5	Predicted Yes	59	13	Predicted Yes	67	10
Recognized 7.94%	Realized 8.93%		Recognized 16.05%	Realized 18.06%		Recognized 11.90%	Realized 12.99%	
2000	Actual No	Actual Yes	2001	Actual No	Actual Yes	2002	Actual No	Actual Yes
Predicted No	1132	69	Predicted No	1113	68	Predicted No	1140	65
Predicted Yes	60	7	Predicted Yes	53	14	Predicted Yes	60	10
Recognized 9.21%	Realized 10.45%		Recognized 17.07%	Realized 20.90%		Recognized 13.33%	Realized 14.29%	
2003	Actual No	Actual Yes	2004	Actual No	Actual Yes	2005	Actual No	Actual Yes
Predicted No	1042	52	Predicted No	1168	65	Predicted No	1235	63
Predicted Yes	49	16	Predicted Yes	62	11	Predicted Yes	60	17
Recognized 23.52%	Realized 24.62%		Recognized 14.47%	Realized 15.07%		Recognized 21.25%	Realized 22.08%	
2006	Actual No	Actual Yes	2007	Actual No	Actual Yes	2008	Actual No	Actual Yes
Predicted No	1251	63	Predicted No	1373	74	Predicted No	1246	80
Predicted Yes	62	17	Predicted Yes	73	14	Predicted Yes	68	12
Recognized 21.25%	Realized 21.52%		Recognized 15.91%	Realized 16.09%		Recognized 13.04%	Realized 15.00%	
2009	Actual No	Actual Yes	2010	Actual No	Actual Yes			
Predicted No	1393	76	Predicted No	1345	69			
Predicted Yes	77	15	Predicted Yes	73	15			
Recognized 16.48%	Realized 16.30%		Recognized 17.85%	Realized 17.05%				

Table 4: Annual returns when removing predicted extreme movers

This table presents the annual, value-weighted returns and the annualized standard deviation of daily returns, by year (in percentage terms), for two portfolios. First, the full sample of firms is utilized which includes all firms with returns data, as well as data for all the predictors utilized in Tables 2 and 3. In the second sample, all firms which are predicted to be extreme movement firms, based on the estimated coefficients of predictors from the previous year, are removed from the sample before returns and standard deviations are calculated. These are the firms predicted to have the highest 3% or lowest 2.5% of returns or delist due to bankruptcy or bankruptcy-like reasons. Predictions are based on coefficients from the probit regression of the prior year and the variable values from the last trading day of the previous year. The mean is the geometric mean of the annual returns.

	All Firms		No Extreme Movers		Difference	
	Ret	Ann SD	Ret	Ann SD	Ret	Ann SD
1997	31.23	19.54	32.02	17.23	0.79	-2.31***
1998	26.22	23.44	27.13	20.11	0.91	-3.33***
1999	23.03	26.22	20.82	25.42	-2.21	-0.80*
2000	-10.22	24.12	-6.78	23.67	3.44	-0.45
2001	-11.32	27.73	-9.45	26.1	1.87	-1.63***
2002	-24.15	21.04	-22.18	20.03	1.97	-1.01**
2003	29.87	20.44	26.68	18.45	-3.19	-1.99**
2004	7.23	18.77	8.34	17.82	1.11	-0.95**
2005	6.65	17.74	7.22	16.12	0.57	-1.62***
2006	16.83	18.72	17.24	17.44	0.41	-1.28**
2007	4.56	22.03	5.72	20.14	1.16	-1.89***
2008	-40.64	46.12	-40.02	44.92	0.62	-1.20***
2009	28.11	47.70	27.87	47.26	-0.24	-0.44
2010	16.48	31.46	16.59	30.04	0.11	-1.42***
Mean	4.99	26.08	5.70	24.63	0.71	-1.45***

*, ** and *** denote statistically lower annualized day-to-day standard deviation of returns at the 10%, 5% and 1% levels, respectively.

Table 5: Directional Fama-Macbeth results

This table presents coefficients and t-stats of the Fama-Macbeth procedure which conducts annual probit regressions of the likelihood of a firm being an extreme return firm. Models are estimated separately for positive and negative extreme return predictions. Firms in the highest 6% of equity returns are considered extreme positive return firms while firms in the lowest 5.5% of equity returns, or delisting for bankruptcy or bankruptcy-like reasons, are considered extreme negative return firms. The sample period considers returns for 1997 through 2010 with predictor variables measured on the last trading day of the previous year. BM is the book-to-market ratio, Disp is the analyst forecast dispersion, IV is the implied volatility of the call option closest to at-the-money expiring in February of the following year, Size is the log of firm size (in millions of dollars), Age is log of firm age in months, Vol is the log of the average number of shares traded daily in the previous year (in millions), RD is the research and development expense of firms in the previous year in millions of dollars, and Price is the log of firm price.

	Positive		Negative	
	Coefficient	t-value	Coefficient	t-value
Intercept	-2.311	(-0.97)	-3.484	(-1.83)
BM	2.773	(1.02)	0.621	(1.22)
Disp	-4.304	(-2.44)	1.577	(2.33)
IV	1.932	(5.58)	3.552	(7.24)
Size	-0.405	(-2.48)	-0.158	(-2.52)
Age	-0.241	(-2.55)	-0.312	(-4.04)
Vol	0.049	(1.32)	0.068	(1.72)
RD	-0.001	(-1.22)	-0.010	(-0.88)
Price	-0.085	(-0.44)	-0.084	(-0.32)

Table 6: Prediction success for non-directional and directional models

This table presents accuracy results for predicting firms that will have the highest 3% and lowest 2.5% of annual equity returns (or delist for bankruptcy or bankruptcy-like reasons) for two non-directional models. One is the model of Table 3 and the other is the model of Table 3 excluding implied volatility as a predictor. Results are also presented for positive and negative extreme return prediction models (using the predictive variables of the Table 3 model) separately which seek to identify the highest 6% and lowest 5.5% of annual equity returns (or delist for bankruptcy or bankruptcy-like reasons). At the beginning of each year, the probit regression coefficients from the previous year are used to predict which firms will exhibit extreme returns in the following year. The percentage of extreme return firms that correctly were predicted to be so in the given year are classified as "recognized". The percentage of predicted extreme return firms that exhibit extreme price movements firms are classified as "realized".

Non-Directional	Actual No	Actual Yes	Non-Directional (no IV)	Actual No	Actual Yes
Predicted No	16,955	944	Predicted No	16,878	1,021
Predicted Yes	874	176	Predicted Yes	951	99
	Recognized	15.71%		Recognized	8.84%
	Realized	16.76%		Realized	9.43%
Positive	**Actual No**	**Actual Yes**	**Negative**	**Actual No**	**Actual Yes**
Predicted No	16,803	1,022	Predicted No	16,854	987
Predicted Yes	1,014	110	Predicted Yes	1,003	105
	Recognized	9.72%		Recognized	9.62%
	Realized	9.79%		Realized	9.48%

Table 7: Annual returns when removing predicted extreme negatives

This table presents the annual, value-weighted returns and the annualized standard deviation of daily returns, by year (in percentage terms), for two portfolios. First, the full sample of firms is utilized which includes all firms with returns data, as well as data for all the predictors utilized in Tables 2 and 3. In the second sample, all firms which are predicted to be extreme negative movement firms, based on the estimated coefficients of predictors from the previous year, are removed from the sample before returns and standard deviations are calculated. These are the firms predicted to have the lowest 5.5% of returns or delist due to bankruptcy or bankruptcy-like reasons. Predictions are based on coefficients from the probit regression of the prior year and the variable values from the last trading day of the previous year. The mean is the geometric mean of the annual returns.

	All Firms		No Extreme Negative		Difference	
	Ret	Ann SD	Ret	Ann SD	Ret	Ann SD
1997	31.23	19.54	32.14	17.74	0.91	-1.80**
1998	26.22	23.44	27.41	22.79	1.19	-0.65
1999	23.03	26.22	19.85	26.78	-3.18	0.56
2000	-10.22	24.12	-6.18	24.34	4.04	0.22
2001	-11.32	27.73	-9.77	26.44	1.55	-1.29**
2002	-24.15	21.04	-21.79	19.68	2.36	-1.36***
2003	29.87	20.44	28.02	18.91	-1.85	-1.53***
2004	7.23	18.77	9.03	18.44	1.80	-0.33
2005	6.65	17.74	6.89	17.90	0.24	0.16
2006	16.83	18.72	17.68	18.53	0.85	-0.19
2007	4.56	22.03	5.67	22.34	1.11	0.31
2008	-40.64	46.12	-39.82	46.01	0.82	-0.11
2009	28.11	47.70	27.92	47.34	-0.18	-0.26
2010	16.48	31.46	16.60	30.74	0.12	-0.72
Mean	4.99	26.08	5.88	25.57	0.89	-0.50

*, ** and *** denote statistically lower annualized day-to-day standard deviation of returns at the 10%, 5% and 1% levels, respectively.