Two Essays on Asset Prices

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ABSTRACT

This dissertation consists of two chapters. The first chapter examines the role of growth options on stock return continuation. Growth options are both difficult to value and risky. Daniel, Hirshleifer and Subrahmanyam (1998) argue that higher momentum profits earned by high market-to-book firms stem from investors' higher overconfidence due to the difficulty of valuing growth options. Johnson (2002) and Sagi and Seasholes (2007) offer an alternative rational explanation wherein growth options cause a wider spread in risk and expected returns between winners and losers. This paper suggests that firm-specific uncertainty helps disentangle these two different explanations. Specifically, the rational explanation is at work among firms with low firm specific uncertainty. However, the evidence is in favor of the behavioral explanation for firms with high firm specific uncertainty. This is consistent with the notion that investors are more prone to behavioral biases in the presence of firm-specific uncertainty and the resulting mispricings are less likely to be arbitraged away.

The second chapter examines how investors capitalize differences of opinion when disagreements are common knowledge. We conduct an event study of the market's reaction to analysts' dispersed earnings forecast revisions. We find that investors take differences of opinion into account and do *not* exhibit an optimism bias. Our findings indicate that the overpricing of stocks with high forecast dispersion is not due to investors' tendency to overweight optimistic expectations, but rather due to investor credulity regarding analysts' incentives. Our findings support the notion that assets may become mispriced when rational investors face structural uncertainties as proposed by Brav and Heaton (2002).

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Chapter 1

What Drives the Enhanced Momentum Profits of Growth Firms? Mispricing or Risk

1.1 Introduction

Jegadeesh and Titman (1993), using a U.S. sample of NYSE/AMEX stocks for the period 1965 to 1989, document that a strategy of buying stocks with recent high returns and selling those with recent low returns yields statistically and economically significant profits. Following this study, many studies have documented the existence and robustness of momentum profits in many other stock markets around the world.[1] Although the profitability of momentum strategies is not very controversial, what drives it is less clear. Both risk-based and behavioral theories have been proposed in search of an explanation for the positive autocorrelation in stock returns.[2]

Momentum profits vary within the cross-section of firms. There is an extensive literature documenting that momentum profits can be enhanced by choosing recent winners and losers strategically based on firm-specific variables. For example, momentum profits are found to be closely related to trading volume (Lee and Swaminathan, 2000), the market-to-book ratio (Asness, 1997, Daniel and Titman, 1999), analyst coverage and firm size (Hong, Lim and Stein, 2000), and dispersion in analysts' earnings forecasts (Verardo, 2009).

A particularly material relation is the one between market-to-book ratio and momentum. Although higher momentum profitability among high market-to-book firms is empirically well-documented, the underlying reasoning is not clear. Two prominent explanations differ with respect to their assumptions regarding investor rationality. Daniel, Hirshleifer, and Subrahmanyam (1998; hereafter DHS) and Daniel and Titman (1999) argue that this momentum profitability differential is due to the larger mispricing of securities with more opaque information environments, e.g., high market-to-book firms have more growth options. Lack of tangible information, in turn, makes investors holding those stocks more susceptible to behavioral biases, particularly overconfidence. For example, Einhorn (1980) suggests that overconfidence tends to be more severe for tasks that require more judgment and less for

[1] Rouwenhorst (1997, 1998) documents the existence of momentum for 20 emerging markets and European countries. Chui et al. (2000) finds the return continuation for several Asian markets. Jegadeesh and Titman (2001) show that momentum profits persist for the U.S. market following their initial sample period.
[2] Among these are Daniel, Hirshleifer and Subrahmanyam (1998), Barberis, Shleifer and Vishny (1998), Hong and Stein (1999), Hong and Stein (2007), Johnson (2002), Berk, Green and Naik (1999), Sagi and Seasholes (2007).

mechanical tasks such as solving arithmetic problems. According to the DHS model, overconfidence and self-attribution biases may cause mispricings and return continuation in the following way. First, overconfident investors overreact to their private information. Furthermore, the self-attribution bias of investors, which is supported by evidence from the psychology literature, causes them to attribute successes to their own skill and perceive failures as sabotages. This implies that confidence, on average, increases over time as news arrive, which in turn causes a further overreaction and return continuation. The prima facie implication of this model is an overreaction to both good and bad news. However, we could expect under reaction to negative disconfirming news as long as prices are determined by the most optimistic buyers with self-attribution bias.[3]

Johnson (2002) offers a rational mechanism whereby the existence of risky growth options may cause the observed momentum returns. According to this model, winners have higher expected growth rates than losers. Moreover, the log firm value is a convex function of expected growth rates, implying an increasingly sensitive relation between expected returns and growth rates when the growth rate is higher.[4] Therefore, winners have higher growth rate risk and expected returns than losers if expected growth rate risk carries a positive premium. Using a similar insight that does not rely on investor irrationality, Sagi and Seasholes (2007) argue that growth options, which are riskier than assets-in-place, tend to increase in value more for firms that have recently performed better. Hence, past winners have higher risk and expected returns than past losers. According to this rationale, the spread between winners and losers in terms of risk and expected returns is expected to be larger for firms with more growth options.

While the behavioral theory does not discriminate between losers and winners in terms of their contribution to the momentum profitability differential between value and growth firms, the rational explanation predicts this differential to originate primarily from recent winners. In both Johnson (2002) and Sagi and Seasholes (2007), the convex relation between log firm value and

[3] This is likely to be the case for most types of recurring events such as announcements of earnings, dividends and analyst forecasts. However, it may not be true for extreme non-recurring events where overconfident short-sellers may cause an overreaction to negative news. In our opinion, this latter scenario is unlikely to persist and create the patterns of momentum profits that are observed over six to twelve months period.

[4] In its simplest form, convexity can be shown by using Gordon (1962) deterministic dividend growth model: $p = \frac{d}{k-g}$ where p is stock price, d is dividend, k is discount rate and g is growth rate. Let $Y = \frac{p}{d}$ be the price dividend ratio. Then, $\frac{\partial \ln Y}{\partial g} = \frac{1}{k-g}$ and $\frac{\partial^2 \ln Y}{\partial g^2} = \frac{1}{(k-g)^2} > 0$.

growth rate assigns a central role to winners in generating momentum profits if shocks in growth rates are positively related to past price changes. In a similar vein, this convex relation implies that growth winners are expected to show greater return persistence than value winners since winners with more growth options are more likely to experience larger positive changes in their expected growth rates, which will in turn cause greater increases in their risk and hence expected returns. Moreover, the increasing risk due to the presence of a valuable growth option dominates the decreasing risk effect of leverage for winners. The same convex relation, on the other hand, implies that the prediction of growth options based risk explanation for losers is not as strong as that for winners. This argument is intuitive because for the same level of past performance, growth losers are likely to have higher expected growth rates than value losers.

Despite the central role growth options appear to play for the momentum phenomenon, the existing empirical literature is not able to discriminate between the behavioral and risk-based explanations. In this paper, we focus on the role of idiosyncratic volatility in the relation between return continuation and growth options. We expect idiosyncratic volatility to be a central factor shaping the relation between momentum profits and market-to-book for at least two reasons. First, to the extent that firms with high idiosyncratic volatility are more difficult to value, behavioral biases would interfere more with the pricing of these securities. Hence, behavioral theories predict greater mispricings and momentum for firms with high idiosyncratic volatility. Second, Shleifer and Vishny (1997) and Pontiff (2006) assign idiosyncratic volatility an important role in limiting arbitrage. In the Shleifer and Vishny (1997) model, idiosyncratic volatility deters arbitrage activity since arbitrageurs are poorly diversified. Moreover, Pontiff (2006) argues that the willingness of a risk-averse arbitrageur to allocate capital to a mispriced security would be less for high idiosyncratic volatility stocks regardless of the number of stocks in his portfolio. Therefore, both greater behavioral biases and lower probability of arbitrage are expected to contribute to the mispricing of stocks with high idiosyncratic volatility.[5]

We find evidence supporting both behavioral and risk-based explanations, albeit for firms that differ with respect to their idiosyncratic volatility. Using independent sorts and Jegadeesh and Titman (1993) calendar-time momentum strategies, we find an asymmetric contribution of losers and winners into the momentum profitability differential between value and growth firms

[5] Ali, Hwang and Trombley (2003) argue that idiosyncratic volatility limits arbitrage and contributes significantly to the value premium. Also, Daniel and Titman (2006) show that book-to-market ratio owes its predictive ability of future returns to being a strong proxy for past intangible returns.

in relation to idiosyncratic volatility. For firms with low idiosyncratic volatility, past winners are the primary drivers of the momentum profitability differential between value and growth firms. Portfolio analysis indicates that growth firms earn 0.47% (t-statistic=3.13) more abnormal momentum returns per month compared to value firms and value winners underperform growth winners by 0.39% (t-statistic=3.62) abnormal returns per month. On the other hand, past losers generate the momentum differential between value and growth firms with high idiosyncratic volatility. That is, growth firms earn 0.39% (t-statistic=2.68) more abnormal momentum returns per month than value firms and losers of growth firms underperform those of value firms by 0.46% (t-statistic=3.72) abnormal returns per month.

The behavioral explanation predicts subsequent reversals of momentum profits. For example, Hirshleifer (2001) contends that one central prediction of recent behavioral theories is that firms with larger momentum should experience greater reversals. If growth firms have higher momentum due to more severe mispricings, then we should expect growth firms to have greater reversals as well. On the other hand, the rational explanation based on growth options does not predict reversals. For example, Johnson (2002) argues that growth rate shocks should be sufficiently persistent in order to generate initial expected return spread between winners and losers. In the period subsequent to the initial momentum holding period, we find that growth stocks as a whole experience reversals, and these reversals are concentrated in those with high idiosyncratic volatility. The nonexistence of reversals in growth firms with low idiosyncratic volatility provides further support for the rational explanation. Furthermore, reversals among high idiosyncratic volatility firms are mostly confined to growth firms, which suggest that both growth options and idiosyncratic volatility play independent roles in creating momentum through mispricings.

We further show that winners are the major source of reversals among growth firms with high idiosyncratic volatility. For example, winners in this group earn 0.48% (t-statistic=4.37) abnormal returns per month during the first six months after portfolio formation. Subsequently, they lose 0.12% (t-statistic=1.09) abnormal returns per month in the following six months. During the second year, they go on to underperform by 0.40% (t-statistic=3.08) abnormal returns per month. In contrast, growth losers with high idiosyncratic volatility experience drifts in abnormal returns for the first year following portfolio formation and no statistically significant reversals thereafter.

A possible alternative explanation for the reversals of winners may be based on a recent different line of literature which suggests that firms with valuable risky growth options experience declines in risk upon exercising growth options (Carlson, Fisher, and Guimmerano (2004, 2006)). Inconsistent with this argument, we show that both low- and high-investing growth firms with high idiosyncratic volatility experience reversals. Furthermore, firms with the same level of high investment but with low idiosyncratic volatility do not show subsequent underperformance. These findings suggest that Carlson et al. (2004, 2006) explanation is not the primary driving force behind the reversal of winners.

In a nutshell, this paper documents that:

(i) Among firms with high idiosyncratic volatility, higher momentum profits earned by growth firms are primarily due to the poor performance of past losers.

(ii) Among firms with low idiosyncratic volatility, the difference in winners drives the higher momentum profits of growth firms.

(iii) There is no evidence of reversals for growth firms with low idiosyncratic volatility.

(iv) There is a significant reversal of momentum profits for growth firms with high idiosyncratic volatility.

(v) The primary source of this reversal is the subsequent underperformance of past winners.

Overall, our findings provide support for the major role of idiosyncratic volatility in disentangling two different explanations. Among firms with low idiosyncratic volatility, the greater contribution of past winners to the momentum profitability differential between value and growth firms and the non-existence of reversals in subsequent periods are consistent with risk-based explanations of Johnson (2002) and Sagi and Seasholes (2007). On the other hand, among firms with high idiosyncratic volatility, both reversals of growth winners and the larger drift of growth losers are consistent with the behavioral explanation in the manner that growth options result in greater overconfidence due to their difficulty of valuation. These findings suggest that the behavioral explanation is at play through both overreaction to positive news and underreaction to negative news. In other words, the joint effect of growth options and idiosyncratic volatility is more likely to result in overpriced securities than underpriced ones.

We structure the rest of the paper in four sections. Section 2 discusses the data, methodology, definition of variables and market states. Section 3 presents the main empirical findings. Section 4 concludes the paper.

1.2 Data

Stock return data for NYSE, Amex and Nasdaq stocks are extracted from the Center for Research in Security Prices (CRSP) monthly stock files. Following standard convention, we limit our analysis to common stocks with share codes of 10 and 11 in the CRSP U.S. Stock database.[6] We exclude stocks with share prices below \$5 and market capitalizations below the 10^{th} NYSE size percentile at the beginning of the holding period to minimize the market microstructure based concerns.[7]

All accounting information is from COMPUSTAT annual files. Following Daniel and Titman (2006), we define a firm's market-to-book ratio as the market value of equity based on CRSP data at the end of December of year t divided by the total book value of the equity at the firm's fiscal year end in year t. We compute the book value of equity in the following way. We first obtain shareholders' equity. We use stockholders' equity (data216) for shareholder's equity. If it is missing, we sum Total Common Equity (data60) and Preferred Stock Par Value (data130). If either of them is missing, we subtract Total Liabilities (data181) from Total Assets (data6). If none of these three ways yield non-missing values, we take the book value of equity as missing. Then, book value of equity is computed as subtracting the preferred stock value from shareholders' equity. We first try redemption value (data56) for the preferred stock value. If it is not available, we try liquidating value (data10) and finally carrying value (data130). If all three measures of preferred stock value are missing, we treat book value of equity as missing. Finally, we add balance sheet deferred taxes (data35) to this value, if available.

The next primary variable of interest is the idiosyncratic volatility of a firm. Following McLean (2010), we compute idiosyncratic volatility as the standard deviation of the residuals obtained from the regression of monthly returns of individual stocks on the S&P 500 index returns over the past 36 months prior to the portfolio formation date. We call this variable "mivol". This restricts our sample to firms having at least three years of return data in CRSP. We

[6] We exclude American Depository Receipts (ADRs), Shares of Beneficial Interest (SBIs), certificates, Real Estate Investment Trusts(REITs), closed-end funds, and companies incorporated outside the U.S.

[7] Using 10th or 20th NYSE/Amex size cut-off points does not materially affect the results.

replicate our results by using a single factor market model and Fama and French (1993) three factor model. Since the results do not alter materially, we report only the results obtained from "mivol".[8]

We estimate systematic risk, beta, as in Fama and French (1992). We first find the preranking betas by using the previous 60 months of returns in the market model. We then assign stocks to 10*10 portfolios on the basis of size and preranking betas each June of year t. Firm size is measured by the market value of equity (the product of the month end price and outstanding number of shares). Next, we compute the equal-weighted returns for each portfolio from July of year t to June of year t+1. We run full sample regressions of the portfolio return on the current and one month lagged market returns. The sum of the two slopes is assigned to all stocks within that portfolio. We include lagged market returns in order to prevent problems associated with nonsynchronous trading (Dimson, 1979).

We follow the Jegadeesh and Titman (1993) calendar-time methodology in calculating momentum profits. This methodology produces a time-series of monthly momentum returns while avoiding biases in standard errors due to autocorrelation, which makes it possible to use conventional standard errors to evaluate the statistical significance of momentum returns. For each month in the sample period, we rank stocks into quintiles based on the cumulative returns over the past J months (formation period). The top performing quintile is called winner and those in the worst performing one is called loser portfolio. These portfolios are held for the next K months (holding period). We skip a month between formation and holding periods to avoid problems due to microstructure effects. Since new portfolios are formed in each month, we measure the return on a momentum portfolio in a given calendar month as the equal weighted average of K portfolios that remain open in that calendar month. For example, the month t+1 momentum return (e.g., loser or winner quintile) is the equal-weighted average of the month t+1 returns of portfolios formed at months t-6, t-5, t-4, t-3, t-2 and t-1. This is equivalent to revising 1/K of a portfolio each month. To determine whether the covariances between momentum portfolios and possible risk factors play significant roles in the observed patterns, we estimate the abnormal returns based on Fama and French (1993) three-factor model. Specifically, we run the following time-series regression using monthly returns:

[8] We also measure the idiosyncratic volatility by skipping the last six months. Our findings do not change significantly.

$$R_{p,e,t} = \alpha_{p,t} + \beta_{mkt} \times (R_{m,t} - r_{f,t}) + \beta_{SMB} \times SMB_t + \beta_{HML} \times HML_t + \varepsilon_{p,t}$$

where $R_{p,e,t}$ is the excess monthly return for portfolio p; $(R_{m,t} - r_{f,t})$ is the excess market return; SMB is the Fama-French small firm factor; and HML is the Fama-French value factor.[9]

We pay particular attention to the state of the market since both behavioral and risk-based models predict higher momentum returns in up markets. Gervais and Odean (2001) argue that investors may become more overconfident in up states since they, in the aggregate, are in long positions. So, if overconfidence is the source of momentum returns, DHS predict higher momentum in up markets. In the Hong and Stein (1999) model, the overreaction is due to trend-chasing by "momentum traders". They further argue that the level of this overreaction decreases with the risk-aversion of momentum traders. To the extent that risk aversion declines with wealth (Campbell and Cochrane, 1999, and Barberis, Huang and Santos, 2001), this model predicts lower momentum returns following low market returns.[10] On the risk-based side, Sagi and Seasholes (2007) argue that growth options are more abundant and easier to access following market gains, leading to the expectation of greater momentum returns in up markets.

Consistent with the predictions of these theories, previous literature has documented empirical evidence that momentum profits are related to market states. Chordia and Shivkumar (2002) argue that macroeconomic indicators can explain a significant part of momentum profits. However, Cooper et al. (2004) show that the explanatory power of a macroeconomic model is not robust to common filters that are used to mitigate market microstructure biases (i.e., skipping a month between formation and holding periods or one dollar price screen). Cooper et al. (2004) suggest that investors' behavioral biases will be greater following market gains. Using a sample period of 1929 to 1995, they show that momentum profits are nonexistent in down markets, categorized as such if the previous three-year market return is negative. Furthermore, they show that momentum returns are statistically significant except for the lowest quintile on the basis of

[9] We obtain the time-series of SMB, HML and excess market returns from Kenneth French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/). For details on portfolio construction, see Fama and French (1993).

[10] According to the Barberis, Shleifer, and Vishny (1998) framework, momentum and subsequent reversals may be a result of conservatism and representativeness biases. In that model, investors overreact to low weight – high strength news and underreact to high weight – low strength news. This argument is based on Griffin and Tversky (1992) who use recommendation letter example to clarify the weight and strength of new information. The 'weight' refers to the credibility of the letter writer and 'strength' refers to the level of positivity of the letter. As Cooper et al. (2004) argue, testing the implications of this model requires identification of news according to their strength and weight. Similarly, it is also not clear whether there is a relation between growth options and types of news. Furthermore, conservatism bias is expected to be greater for more solid firms such as value firms.

market returns during the prior three years. Similarly, Antonio et al. (2010), using the Conference Board sentiment data and sample period of 1967-2008, show that momentum profits are not observed within the lowest 30% of market states on the basis of sentiment. Following Cooper et al. (2004), we calculate the return of the value-weighted market returns including the dividends over the 36-month period prior to the beginning of the momentum strategy's holding period.[11] We sort holding periods into quintiles based on this return. If that return falls into the bottom 20% of market returns, we classify it as a down state. The remaining four quintiles are classified as up states.[12]

In Panel A of Figure 1.1, we present the number of down states in each calendar year for the period 1965 to 2010. These figures show that down months are clumped in three periods. The first is the 1970s where Western countries experienced recessions due to the oil embargoes by the Arab countries in 1973. The second is 2000s which coincides with the burst of the dot-com bubble. Finally, the late 2000s experience a financial crisis related to the securitization of real estate mortgages and irresponsible lending practices by financial institutions. Many economists refer to this period as "Great Recession". In sum, it is almost unquestionable that there is much less overconfidence and growth options during and following these periods. Panel B of Figure 1.1 plots the equally-weighted momentum returns across different market states. This figure shows that momentum profits are nonexistent only within the bottom 20% of market states. Similarly, momentum profits in growth firms are statistically significant in all market states except the worst quintile of states.

Panel A of Table 1.1 reports raw and abnormal momentum profits separately for up and down states. Using the entire sample period 1965 to 2010 including all 552 months, the equally-weighted calendar-time momentum strategies (J=6, K=6) yield a raw monthly return of 0.75% with a t-statistic of 4.56. The Fama-French (1993) three-factor adjustment does not explain the profitability of momentum strategy: The monthly abnormal return is 0.90% with a t-statistic of

[11] The correct definition of a market state is an empirical issue. In our untabulated results, we find that when past 12 months market return is at its top 50% and past 36 months market returns is at the bottom 20%, momentum strategies are not profitable. On the other hand, the reverse case produces significant momentum profits. Furthermore, the correlation between Baker and Wurgler (2007) sentiment index and past 12 month return is only 0.03. However, it is 0.36 for past 36 month return. Similar values hold for Conference Board sentiment index.

[12] We also tried classifying a down state if the previous market return is negative. This decreases the number of observations but doesn't change the results for both up and down markets. In another definition, for example, for the (J=6, K=6) strategy and the holding month of December 2000, we take the average of the past 36 months cumulative market returns for each of the previous 6 months, skipping a month, October, September, August, July, June, and May of 2000. Results remain the same qualitatively.

5.51. Conditioning on market states confirms that momentum strategies do not work in down states. The Fama-French 3-factor alpha is 1.14 % (t-stat=6.67) in up states, whereas it is -0.07% (t-stat=-0.17) in down states.

In Panel B of Table 1.1, we report the sample summary statistics for up and down states. Consistent with the argument that firms become closer to exercising their growth options in up states, investment ratios measured as the ratio of the sum of capital expenditures and research and development expenses to the total assets are, on average, 25% more in up markets. Similarly, sales growth and profitability measures such as return on assets and return on equity are greater in up states. There is also a significant difference between up and down states in terms of wealth change during the past three years, consistent with more overconfidence and less risk aversion arguments in up states. Furthermore, down states are associated with higher volatilities consistent with Bekaert and Wu (2000). In sum, the nonexistence of momentum profits both at the overall and within growth firms require us to focus on up states in order to be better able to understand the underlying process of the momentum profitability differential between value and growth firms.

1.3 Main Results

1.3.1. Market-to-book and momentum returns

This section presents evidence on how momentum returns vary across firms with different market-to-book ratios which are used as a proxy for the presence of valuable growth options. We form momentum portfolios by independently sorting stocks on the basis of previous six months cumulative returns and market-to-book ratios. The market-to-book ratio is measured at the end of December of year t-1 and used for 12 portfolio formation months from June of year t to May of year t+1.[13] The lag between measurement of market-to-book and forming portfolios is to ensure that our tests do not have a look-ahead bias. We use quintiles in each direction, yielding twenty five portfolios. We follow the calendar-time approach as discussed in detail in the previous section to obtain reliable inferences for statistical significance that addresses the potential serial correlation problem due to overlapping return periods. Table 1.2 reports the Fama-French (1993) three-factor alphas for both up and down markets.

[13] Using market values measured at the prior month do not affect our findings.

Panel A of Table 1.2 shows that momentum profits in up states are statistically significant in all market-to-book quintiles and strengthen with the market-to-book ratio. The abnormal momentum returns are 0.83% (t-statistic=4.90) per month for value (low market-to-book) firms and 1.48% (t-statistic=7.49) for growth (high market-to-book) firms. The difference in monthly abnormal returns between value and growth firms is 0.65% (t-statistic=4.08). On the other hand, momentum strategies in down states do not yield significant profits in any of the quintiles based on market-to-book ratios. For example, value firms earn 0.33% abnormal momentum returns per month but its t-statistic is only 0.78.[14]

The momentum profitability differential between growth and value firms is entirely due to the difference in the performance of losers. Growth firms with the lowest past returns earn -0.94% (t-statistic=-6.64) monthly abnormal returns whereas value firms earn -0.37% (t-statistic=-3.10). This yields a difference of -0.57% (t-statistic=-4.57) which constitutes 87.6% of the momentum profitability differential between growth and value firms. On the other hand, there is no statistically significant difference between winners of growth and winners of value firms.

The observation that the momentum differential between growth and value firms is primarily due to the difference in losers is not consistent with the growth options based risk explanation. As long as growth options are riskier and winners are better able to undertake these options, there should be a difference in terms of return persistence across winners with different levels of growth options.[15] According to the risk-based explanation, winners with more growth options are expected to have greater growth rates than winners with less growth options. Hence, the increase in expected returns should be larger for winners with more growth options. On the other hand, the difference in losers with different levels of growth options seems to be more consistent with behavioral theory which predicts stronger persistence in returns of growth firms for both losers and winners. In untabulated results for this 5*5 analysis, we find that there are strong reversals of momentum profits of growth firms in the second year following the formation

[14] Results do not change materially when we use 3*5, 5*3, 3*3, or 3*4 sortings.

[15] In addition to the convex relation between expected growth rates and expected returns, the positive relation between growth options and risk may be motivated by two different arguments. First, Dechow, Sloan, and Soliman (2004) and Berk, Green, and Naik (2004) argue that the longer duration of future cash flows expected to arise from growth options cause a higher sensitivity to interest rates and consequently higher betas. Second, Carlson, Fisher, and Giammariono (2004, 2006) argue that the presence of embedded options, such as delaying or expanding growth options, have higher implicit leverage than assets-in-place, which in turn causes a higher risk.

month. Furthermore, primary drivers of these reversals are those that have performed better. To this end, the two-way sorting provides evidence supportive of the behavioral explanation in the sense misreactions increase with growth options. In particular, there is more overreaction (underreaction) to past winners (losers) with more growth options.

1.3.2. Idiosyncratic volatility and momentum returns

In this section, our focus is on the relationship between idiosyncratic volatility and momentum returns. Similar to the previous section, we adopt the Jegadeesh and Titman (1993) calendar-time strategy with six month formation and holding periods and using independent sorts of firms into quintiles on the basis of idiosyncratic volatility and past returns. Table 1.3 reports the Fama-French (1993) three-factor alphas separately for both up and down markets.

Panel A of Table 1.3 shows that momentum returns increase with idiosyncratic volatility. Momentum strategies yield 0.54% (t-statistic=3.60) abnormal monthly returns for low idiosyncratic volatility stocks. The same figure is 1.37% (t-statistic=7.97) for high idiosyncratic volatility stocks. The difference in monthly abnormal returns between high- and low-idiosyncratic volatility stocks is 0.83% (t-statistic=5.03). Similar to market-to-book sorting, the source of the difference is the difference in losers. Losers with high idiosyncratic volatility earn -0.91% (t-statistic=-6.27) monthly abnormal returns and losers with low idiosyncratic volatility earn -0.22% (t-statistic=-1.89). The difference is -0.69% (t-statistic=-4.35), which is 84.2% of total momentum profitability differential between low- and high- idiosyncratic volatility stocks. The difference in winners is only 0.13% and not statistically significant. Momentum strategies in down states do not yield statistically significant results in any of the idiosyncratic volatility groups.

The increasing momentum returns with idiosyncratic volatility is consistent with the behavioral models including DHS, Hong and Stein (1999), Barberis, Shleifer, and Vishny (1998).[16] DHS model suggests that over-confidence and self-attribution bias leads to delayed overreaction leading to the return autocorrelation. To the extent that stocks with high

[16] In two recent studies that investigate the relation between idiosyncratic volatility and momentum, Arena, Haggard and Yan (2008) and McLean (2010), researchers find conflicting results. As McLean (2010) argue, the difference is due to the exclusion of small and low-priced stocks which have higher idiosyncratic volatilities. Our findings are consistent with Arena et al. (2008) who find higher momentum profits among high idiosyncratic volatility stocks. None of these studies investigate the effect of interaction between market-to-book and idiosyncratic on momentum returns.

idiosyncratic volatility are more difficult-to-value, DHS predict greater behavioral biases resulting in higher momentum and subsequent reversals. Hong and Stein(1999) model assumes two types of traders. First group is newswatchers who base their trades on private information. Second group is trend-chasers who trade according to the changes in prices. In this model, newswatchers underreact to the information under the assumption of gradual diffusion of information. As long as the amount of firm-specific information increases with idiosyncratic volatility, there is more underreaction to news which leads to more return autocorrelation and reversals. Reversals exist in this model because trend-chasers do not know exactly where they are taking positions, either when prices approach the fundamentals or already exceeded the fundamentals. Finally, according to Barberis et al. (1998), conservatism bias leads to underreaction to information and representativeness bias leads to subsequent overreaction. To the extent that firms with high idiosyncratic volatility have more firm-specific information, we expect more initial underreaction and subsequent overreaction leading to greater momentum and subsequent reversals.

Idiosyncratic volatility not only exacerbates the impact of behavioral biases but also limits arbitrage, e.g. Schleifer and Vishny (1997) and Pontiff (2006). To this end, combining heightened behavioral biases and greater amount of firm-specific information with more limited arbitrage leads to the expectation of greater momentum and subsequent reversals for firms with high idiosyncratic volatility. In untabulated results, consistent with Arena et al. (2008), we observe subsequent reversals of initial momentum profits of stocks with high idiosyncratic volatility.

1.3.3. Market-to-book, idiosyncratic volatility and momentum returns

The previous two sections confirm that momentum profits are increasing in both market-to-book ratio and idiosyncratic volatility, and these relationships exist only in up markets. This section investigates to what extent the effect of growth options proxied by the market-to-book ratio of a firm on momentum profitability varies with idiosyncratic volatility. Since both effects are non-existent in down markets, we focus on up markets in order to have a better understanding of the underlying process of the momentum profitability differential between value and growth firms.

As we have discussed, both growth options and idiosyncratic volatility may result in higher momentum due to mispricings. However, growth options may cause momentum through a rational channel as well, which is more attainable in a sample where mispricings are less likely. The rationale for further separation of growth or value stocks into subgroups on the basis of idiosyncratic volatility is founded on the strong association between mispricings and idiosyncratic volatility. Therefore, we examine how the various levels of growth options in the cross-section impacts return persistence in subsamples, one of which is more likely to be affected by mispricings.

To test how the relationship between momentum and growth options change with idiosyncratic volatility, we use calendar-time strategies and independent sortings based on market-to-book, idiosyncratic volatility and past returns. To keep reasonable number of stocks in each portfolio, we employ terciles of market-to-book and idiosyncratic volatility and quartiles of past returns, resulting in thirty six portfolios each month.[17] Table 1.4 shows the Fama-French (1993) three-factor alphas of losers, winners and momentum returns for different market-to-book and idiosyncratic volatility portfolios.

We observe in Table 1.4 that both momentum profits increase with growth options for different levels of idiosyncratic volatility. Within high idiosyncratic volatility firms, the difference is 0.39% (t-statistic=2.68). Similar to the findings in two-way portfolio analysis, the source of the higher momentum profits of growth firms is the severely underperforming losers of growth firms. For example, value losers have -0.45% (t-statistic=-3.40) monthly abnormal returns whereas growth losers experience -0.92% (t-statistic=-6.62) monthly abnormal returns. The difference of 0.47% is highly significant with a t-statistic of 3.72. However, winners, if any, contribute negatively to the difference in momentum returns between value and growth firms. Winners of growth firms earn 0.07% (t-statistic=0.68) less abnormal returns per month than those of value firms.

Within the low idiosyncratic volatility group, the monthly abnormal momentum return difference between value and growth firms is 0.47% (t-statistic=3.13). However, we observe that winners are the main source of the higher momentum profits of growth firms. Winners of growth firms earn 0.56% (t-statistic=5.55) abnormal returns per month whereas winners of value firms

[17] In untabulated results, we confirm the existence of market-to-book and idiosyncratic effects in these new sorting procedures. The difference in monthly alphas between growth and value firms is 0.35% (t=3.01) per month. The same figure is 0.45% (t-stat=4.61).

earn 0.18% (t-statistic=2.12) abnormal returns per month. The difference of 0.39% has a t-statistic of 3.62.[18] On the other hand, losers of growth firms experience -0.28% (t-statistic=-2.40) monthly abnormal returns and those of value firms yield -0.19% (t-statistic=-1.80). The difference is 0.09% with a t-statistic of 0.73. [19]

The strong asymmetry in terms of the source of the momentum differential between value and growth firms has important implications regarding the validity of existing behavioral and risk-based models that attempt to explain the momentum phenomenon. First, the greater contribution of winners to the difference in momentum differential of growth firms gives support for the rational risk-based theories developed by Johnson (2002) and Sagi and Seasholes (2007). Second, the finding that losers are the only ones that cause the higher momentum returns of growth firms suggest that a rational mechanism based on growth options is not observable for firms with high idiosyncratic volatility.

Table 1.5 reports the mean characteristics of momentum portfolios within each of the nine groups independently sorted on the basis of market-to-book and idiosyncratic volatility. Our purpose in this table is to examine the extent to which we are able to control for formation period returns and idiosyncratic volatility in the cross-section while we are changing market-to-book used as a proxy for the presence of growth options. Panel A, B and C show that we are able to control for both formation period returns and idiosyncratic volatility as we move from value to growth firms. For example, for high idiosyncratic volatility firms, value losers have an average idiosyncratic volatility of 14.33% and the same figure is 15.15% for growth losers. For both formation period returns and idiosyncratic volatility, the differences between growth and value stocks are not statistically significant within low and high idiosyncratic volatility subgroups.

Panel A in Table 1.5 shows that mean market-to-book ratios increase monotonically within each idiosyncratic volatility group. For stocks with low idiosyncratic volatility, the mean market-to-book is 0.91 and 3.88 for value and growth winners, respectively. This spread is larger for stocks with high idiosyncratic volatility. For example, the mean market-to-book ratio for growth winners is 4.61. To see whether the higher market-to-book ratios growth firms with high idiosyncratic volatility, in the remaining Panels of Table 1.5, we document how future

[18] We report our main results for the most common used pair of formation and holding period, (J,K)=(6,6). When we use (J,K)=(6,12), the momentum differential between growth and value firms remains statistically significant only for stocks with low idiosyncratic volatility.

[19] In untabulated analysis as a robustness test, we find that excluding the smallest and largest 20% of firms do yield similar results.

investments of momentum portfolios vary with market-to-book and idiosyncratic volatility. We measure future investment as the ratio of the sum of capital expenditures and acquisition expenses. Specifically, we measure investments for each firm at the fiscal year end which is at most six months earlier or five months later than month t+13, whichever is closer to month t+13. We scale it with total assets measured at the beginning of that fiscal year.[20] We scale investments with total assets. We observe higher future investments for winners within each group. Furthermore, high market-to-book firms have higher future investments. These results indicate that both past returns and market-to-book ratios are related to expected growth rates. Although market-to-book ratios are higher for growth winners with high idiosyncratic volatility than those with low idiosyncratic volatility, these panels show that there is no significant difference in terms of future investments. This implies that high market-to-book ratios accompanied with idiosyncratic volatility are more likely to capture long-term mispricings rather than indicating more growth options.

1.3.4. Regression analysis

In this section, we investigate the association between growth options and return continuation in a Fama-MacBeth (1973) multivariate regression framework. Specifically, we run monthly cross-sectional regressions of the individual stocks' average monthly return over the six months (t+1,t+6) on the cumulative return over the previous six months (t-6,t-1) and other firm characteristics including firm size, market-to-book ratio, beta, and idiosyncratic volatility. We take the time-series average of monthly slope coefficients and use Newey-West (1987) methodology to correct standard errors for the autocorrelation induced by overlapping cumulative returns and heteroskedasticity.

We carry out the estimation for the full sample of firms and also separately for firms within high (top tercile) and low (bottom tercile) idiosyncratic volatility groups. We include interaction terms to measure how return continuation varies with growth options. *Growth* and *midmb* are indicator variables for stocks in the top and middle terciles of market-to-book groups, respectively. We also include indicator variables for losers (bottom quartile of past performance)

[20] We find similar results, when we scale investments by the book equity or sales or when we use only capital expenditures in the numerator.

and winners (top quartile of past performance) to examine whether the effect of growth options varies with past performance.

Table 1.6 presents the estimates from four different specifications for the full sample, and low and high idiosyncratic volatility subsamples, separately. The first model shows that return continuation is statistically significant in the full sample and both low and high idiosyncratic volatility subsamples. Model 2 shows that return continuation is higher for high market-to-book stocks than low market-to-book stocks. Consistent with our two-way portfolio analysis, Model 3 shows that there is an asymmetric effect of growth options on return continuation regarding the stock's past performance. In the full sample, the effect of growth options is larger and more significant for losers. In Models 4 and 5, we show that there is no significant impact of growth options on return continuation if a firm is not in losers group. We observe a similar asymmetry for stocks with high idiosyncratic volatility. On the other hand, the asymmetry observed for the full sample and high idiosyncratic volatility subsample reverses for firms with low idiosyncratic volatility where greater return continuation of growth firms is primarily due to winners. For example, the mean slope coefficient on p6ret × growth in Model 2 is 0.004 (t-statistic=2.04), indicating a greater return continuation among growth firms relative to value firms. This coefficient becomes insignificant in Model 4 when we include p6ret × growth × winner which has a slope coefficient of 0.007 (t-statistic=2.40).

1.3.5. Long-horizon performance of momentum portfolios based on market-to-book and idiosyncratic volatility

The central difference between rational and behavioral theories of momentum lies in their predictions of long term performance of momentum portfolios. Conrad and Kaul (1998) hypothesize that the cross-sectional variation in mean returns may play an important role in the observed momentum patterns. Another early paper, Berk, Green and Naik (1999) suggest that slow turnover in firms' projects imply persistence in betas. The rational model in Johnson (2002) where winners have higher expected growth rates than losers does not predict reversals. The same intuition applies to the momentum profits among growth firms. If the momentum spread between value and growth firms is to due to differences in risk, there should be no reversals in the subsequent period. Sagi and Seasholes (2007) model argues that growth firms earn higher momentum profits due to the greater availability of valuable risky growth options.

Sagi and Seasholes (2007) further argue that increase in risk of winners may be temporary as firms lose or exercise their options. However, how much it will take for a firm to experience decreases in risk, upon exercising growth options, is not clear.[21] Furthermore, as growth options are converted into assets-in-place, it is not very likely that the overall riskiness of the firm decreases to a level necessary for significant reversals.

On the other hand, a crucial common prediction in behavioral theories is that momentum is caused largely by mispricings and therefore it should be followed by reversals.[22] For example, according to DHS model, overconfidence and self-attribution bias leading to delayed overreactions may result in over- and under-pricing of securities. In a similar vein, according to These mispricings revert to the fundamental values in the long-term, causing reversals in returns. Existing empirical evidence provides support for the behavioral explanation. Jegadeesh and Titman (1993, 2001) show that momentum profits reverse in the period following the initial holding year, suggesting a mispricing story as the dominating factor of momentum profits.[23]

In this section, we investigate whether conditioning on growth options and idiosyncratic volatility produces results that lead to different inferences. Following the convention in the literature, we use event-time methodology to investigate the long-horizon performance.[24] At the end of each month t-1, we sort stocks into momentum portfolios based on their prior six months cumulative return performance. Skipping month t, we hold these portfolios for the next 60 months from t+1 to t+60 and compute cumulative returns for different test periods. For each holding period month k (event-time month), we obtain a time-series of returns for each portfolio. We obtain estimated factor loadings for each holding period by regressing monthly equally-weighted raw returns on risk factors and a constant. We run these regressions for losers, winners and momentum returns, separately. We then find abnormal returns based on these estimates as the following:

$$\alpha_{k,t} = r_{k,t} - \hat{\beta}_{mkt,k} \times (r_{mkt,t} - rf_t) - \hat{\beta}_{SMB,k} \times (SMB_t) - \hat{\beta}_{HML,k} \times (HML_t)$$

[21] For example, a possibility is multi-stage investment projects which may result in increases in risk due to initial appearance of possibility of such options, then upon exercising risk may increase due to increases in operating leverage.

[22] See Hirsleifer (2001), Bhojraj and Swaminathan (2006) for a review.

[23] See also Cooper et al. (2004) for the reversals in up states.

[24] For example, Lee and Swaminathan (2000), Jegadeesh and Titman (2001) and Cooper et al. (2004) use this methodology to measure the long term performance.

where $\hat{\beta}_{f,k}$ represents the estimated factor loading for event-time k, $r_{k,t}$ is the raw return in month t, and $(r_{mkt,t} - rf_t)$, SMB_t and HML_t are realized Fama-French (1993) three-factor returns in month t. We finally form event-time cumulative returns to momentum strategies, using either monthly raw or abnormal returns in the following way:

$$CAR_{t+K_2} = \sum_{k=K_1}^{K_2} ret_{k,t+k}$$

where $ret_{k,t+k}$ is either the raw or abnormal returns and (K_1, K_2) pairs are (1,12), (13, 24), (25,36), (37,48), (49,60), (37,60) and (13,60). Since cumulative returns are overlapping, we use Newey and West (1987) to obtain heteroskedasticity-and-autocorrelation consistent estimates of standard errors. For example, we set the number of lags to 47 for (K_1, K_2) = (13, 60).

We first examine long-term performance of momentum strategies on the basis of market-to-book in Table 1.7.[25] Results of event-time analysis are consistent with those of calendar-time strategies such that growth firms earn higher momentum returns in terms of both raw returns and 3-factor alphas. During the six months after portfolio formation, growth firms earn 7.48% (t-statistic=10.42) cumulative abnormal momentum returns. The corresponding figure is 5.09% (t-statistic=8.15) for value firms. The differences in both cumulative raw and 3 factor alphas between growth and value firms during the first six months are statistically significant at conventional levels.

We observe significant reversals in cumulative momentum profits among growth firms following the initial holding periods. The cumulative abnormal momentum returns for the four years following the first year of holding is -5.72% (t-statistic=-2.43). Most of the reversals happen in the first two years following the first year of holding. The cumulative abnormal momentum return is -4.39% (t-statistic=-2.10) during that period. As a consequence of the reversal in growth firms, the initial momentum differential between growth and value firms erodes significantly during the same period.

The strong reversals of momentum profits of growth stocks, at first glance, seem to be consistent with the behavioral theories, which attribute mispricings to the heightened behavioral biases driven by the difficulty of valuing these securities. According to these results, a rational

[25] Since our ultimate purpose is to examine the long-horizon performances of growth firms with different levels of idiosyncratic volatility, we use terciles of market-to-book or idiosyncratic volatility and quartiles of past returns to have more comparable results with our previous results of calendar-time strategy in Table 1.4.

model does not receive support. We next investigate whether risk-based explanation may receive support upon sorting stocks into subgroups on the basis of idiosyncratic volatility.

Table 1.8 presents the event-time cumulative raw and 3-factor alphas of momentum portfolios independently sorted by market-to-book and idiosyncratic volatility. In Figure 1.2, we plot the cumulative abnormal returns of portfolios of interest in the event time. Results are striking. First, there is no evidence of reversals of momentum returns for growth stocks with low idiosyncratic volatility. The cumulative raw momentum returns for these stocks during the next two years following the first year after portfolio formation is -1.42% (t-statistic=-0.59) and in untabulated findings, the figure is -2.32% (t-statistic=-0.53) during the next four years following the first year after portfolio formation. The cumulative 3-factor alphas for these two periods are not statistically significant. Second, we find statistically significant reversals for growth stocks with high idiosyncratic volatility and no evidence for reversals for value stocks with high idiosyncratic volatility. The cumulative equally-weighted raw returns for the next two years following the first year after portfolio formation is -12.05% and reliably negative with a t-statistic of -5.02. The cumulative abnormal return during the same period is -8.38% with a t-statistic of -4.29. These results indicate that the reversal of momentum returns within growth stocks is confined to the subgroup of high idiosyncratic volatility. Furthermore, the reversals within high idiosyncratic volatility stocks are mostly due to growth firms. The cumulative abnormal return of value firms with high idiosyncratic volatility is 1.55% with a t-statistic of 0.68 for the same period. These findings point out the importance of the joint existence of growth options and idiosyncratic volatility in creating momentum through mispricings.

1.3.6. Losers vs. Winners in subgroups of growth firms based on idiosyncratic volatility

In the previous section, we have shown that reversals of momentum profits in growth firms are confined to firms with high idiosyncratic volatility. The DHS framework suggests that overreaction due to overconfidence can apply for both winners and losers. In other words, irrational behavior may lead to both overpriced and underpriced stocks which then revert to their fundamental values through time. To examine whether this is indeed the case, we look at the subsequent performance of losers and winners, separately.

Table 1.9 provides evidence that winners are the major drivers of the reversals among growth firms with high idiosyncratic volatility. During the first six months, winners earn 0.48%

(t-statistic=4.37) abnormal returns per month, then they start to experience corrections in the following six months where they lose 0.12% (t-statistic=1.09) and during the second year following portfolio formation they lose 0.40% (t-statistic=3.08) abnormal returns per month. On the other hand, we observe a drift among losers for the first year following portfolio formation. They lose 0.88% (t-statistic=9.95) and 0.47% (t-statistic=3.76) abnormal returns per month during the first six months and the following six months, respectively. In Figure 1.3, we plot the cumulative abnormal returns of losers and winners for growth firms with low- and high-idiosyncratic volatility.

Similar to the losers of growth firms with high idiosyncratic volatility, losers of growth firms with low idiosyncratic volatility experience a drift for the first year following portfolio formation. They lose 0.33% (t-statistic=3.40) and 0.25% (t-statistic=2.52) monthly abnormal returns for the first six months and the following six months following portfolio formation, respectively. More importantly, winners of growth firms with low idiosyncratic volatility do not experience reversals during the next five years following portfolio formation. They initially earn 0.53% (t-statistic=5.36) for the first six months and continue to earn statistically significant positive abnormal returns of 0.34% (t-statistic=3.66) per month in the following six months.

To sum up, the reversals among growth firms with high idiosyncratic volatility are largely due to the underperformance of winners in the subsequent periods. This is indeed consistent with delayed overreaction due to changing overconfidence arising from self-attribution bias as suggested by DHS. On the other hand, the drift in losers of growth firms with high idiosyncratic volatility is more consistent with an underreaction story. This is indeed consistent with the behavioral explanation in the sense that overconfident investors who are in the long positions tend to underweight disconfirming negative news. In the bottom line, we observe that both overreaction to good news and underreaction to bad news increase with growth options when idiosyncratic volatility is high. The nonexistence of reversals among winners of growth firms with low idiosyncratic volatility supports the rational explanation based on growth options suggested by Johnson (2002).

1.3.7. Winners with different investment levels

We have documented that the reversals in initial return continuations are limited to the winners of growth firms with high idiosyncratic volatility. These reversals are confined to the second year (t+13, t+24) following the portfolio formation month (t-1). In a different line of literature, Carlson et al. (2004, 2006) argue that the risk and expected return of a firm may decline upon exercising growth options. In other words, the new assets that arise due to exercising growth options are less risky than expansion opportunities. As long as growth winners with low idiosyncratic volatility have the same level of investment as that of growth winners with high idiosyncratic volatility, our results up to this point suggest that this is not the driving force of reversals of growth winners with high idiosyncratic volatility.

To examine this possibility in a more detailed manner, we investigate the reversals in subgroups of winners on the basis of their investment levels. Specifically, we use capital expenditures scaled by beginning period total assets as a proxy for investment. We measure capital expenditures for each firm at the fiscal year end which is at most six months earlier or five months later than month t+13, whichever is closer to month t+13. We sort winners into terciles based on their investments and report the time-series average of mean investment in each portfolio along with mean abnormal returns during the second year after portfolio formation in Table 1.10.

We find that reversals are not confined to high investing firms. The mean investment for high investing firms is 13.94%, whereas it is 2.44% for low investing firms. However, the mean abnormal return for low- and high- investing firms is -0.35% (t-statistic=-2.53) and -0.58% (t-statistic=-3.01). Furthermore, the difference in future abnormal returns of 0.23% is not statistically significant at conventional levels (p-value=10.81). Although growth winners with low idiosyncratic volatility do not experience reversals as a whole, we investigate whether high investing firms among those exhibit a different pattern. We find no reversals within the high investing firms. These results rule out the possibility that reversals of initial momentum returns are due to decline in risk upon exercising risky growth options.

1.3.8. Profitability of momentum strategies in growth vs. value firms through time

In this section, we present how profitability of momentum strategies within growth and value firms varies over time. We also distinguish between up and down states due to the nonexistence of momentum profits in down states. In figure 1.4, we plot the value over time of $1 invested in momentum strategies that buy winners and sell losers within growth and value firms, separately. The dashed and solid lines represent up and down states, respectively.

There are two outstanding episodes in this graph: one is the first half of 1970s and the second is the recent period after 2002. Both periods mostly coincide with the chaotic periods in macro economy and political environment both in the US and worldwide, in which we expect the general level of overconfidence and growth options are below the historical averages.

The last point that we think worth emphasizing is that momentum strategies can be extremely risky when market conditions are not stable. For example, the overall momentum strategies experience significant losses in April and May of 2009. For example, momentum in growth firms loses 9.66% in March, 2009, 22.71% in April, 2009 and 10.93% in May, 2009. Value-weighted market returns are -9.8%, -18.5%, -8.5%, 2.1%, -7.7%, -10.1%, 8.8%, 11.1%, and 6.7% for the 9 months from September, 2008 to May, 2009. This suggests that momentum portfolios select high beta stocks which tend to be severely underpriced in down markets. When the market reverses its direction, particularly past losers start to cover their losses, resulting in severe losses of momentum strategies in those months where market reverses its direction.

1.4 Conclusion

This paper examines two alternative explanations for the higher momentum profits of firms with high market-to-book ratios. Behavioral theory suggests that the increased overconfidence associated with the difficultly in interpretation of intangible information may lead to overreaction to new information, which results in the mispricing of growth firms. Alternatively, the risk-based explanation suggests that the greater presence of valuable risky growth options leads to a greater spread in risk between past winners and losers. While both explanations predict higher momentum returns for growth firms, risk-based explanation predicts that the momentum profitability differential is due to the greater persistence of growth winners. Moreover, behavioral explanation predicts overreactions and subsequent reversals, while rational explanation does not predict reversals.

We document the major role played by idiosyncratic volatility in disentangling these two widely different explanations. Idiosyncratic volatility is expected to play an important role in momentum profits due to mispricings because (i) an extensive body of research identifies it as the primary hinderance for arbitrageurs in their ability to profit from mispricings and (ii) behavioral theories of momentum predict larger momentum for firms with greater uncertainty.

We show that for firms with low idiosyncratic volatility the momentum profitability differential between value and growth firms is primarily due to the greater return persistence in the returns of growth winners. Furthermore, we do not observe subsequent reversals for these growth winners. On the other hand, when idiosyncratic volatility is high, the momentum profitability differential is due to the greater persistence in returns of growth losers relative to value losers. We further observe reversals of momentum returns among growth firms with high idiosyncratic volatility. These reversals are mostly due to the subsequent underperformance of growth winners.

Our findings suggest that the higher momentum profits of growth firms with low idiosyncratic volatility are consistent with a rational risk-based explanation that employs expected growth rates in deriving the persistence in returns. On the other hand, the heightened overconfidence associated with growth options causes momentum through mispricings for firms with high idiosyncratic volatility. The evidence suggests that these mispricings arise from both overreaction to positive news and underreaction to negative news.

A recent growing theoretical literature attempts to explain the persistence in returns by employing disagreement models. For example, Hong and Stein (2007) suggest that disagreements among investors may cause underreaction to both positive and negative news, which generate return continuation for both past losers and winners. Our findings for growth firms with high idiosyncratic volatility would be more consistent with a model in which both recent winners and losers are held by the most optimistic investors with a self-attribution bias. In this scenario, we would expect an asymmetric effect because these optimistic investors could overreact to positive confirming news and underreact to negative disconfirming news. To the extent that disagreements increase with growth options and idiosyncratic volatility, overreaction in winners and underreaction in losers are expected to be more for stocks with more growth options and higher idiosyncratic volatility.

Overall, we document patterns in returns that are consistent with two different explanations for the effect of growth options on return continuation, while pointing out the importance of joint existence of growth options and idiosyncratic volatility for mispricings. Our findings contribute to two different bodies of research that (i) investigate how return continuation varies within the cross-section of firms and (ii) examine the impact of limits to arbitrage on mispricings.

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Table 1.1 Returns to Price Momentum Portfolios and Descriptive Statistics

The sample includes common stocks traded on the NYSE, Amex and Nasdaq during 1965-2010. Stocks with prices below $5 and with market capitalizations below the tenth percentile of NYSE stocks are excluded. A down state is the one which past 36 month value-weighted market return prior to the holding period falls into the bottom 20% of all months. The remaining 80% is defined as up states. Panel A reports the average monthly equally-weighted returns and Fama-French three factor model alphas with their t-statistics for momentum strategies implemented by Jegadeesh and Titman (1993) calendar-time strategies with (J,K)=(6,6). Panel B reports the time-series equal-weighted averages of momentum portfolios characteristics. Momentum quintiles are formed each month by sorting stocks on p6ret. p6ret is the cumulative return from t-6 to t-1. ln(m/b) is the natural logarithm of the market-to-book ratio measured at the end of December of year t. Mivol is the idiosyncratic volatility obtained by regressing a stock's return on S&P500 index return over the past 36 months prior to portfolio formation. Beta is measured as in FF(1992). Sg is the sales growth in year t. mktlev is the market leverage measured as the ratio of the sum of long term debt and debt in current liabilities to the market value of firm. ROA is the net income divided by total assets. ROE is the net income divided by shareholder's equity. Investment is ratio of the sum of research and development expenses and capital expenditures to total assets. $p(M/B_t, M/B_{t-1})$ is the spearman rank correlation between the current and one year lagged market-to-book ratio. $p(mivol_t, mivol_{t-1})$ is the Spearman rank correlation between the current and one year lagged idiosyncratic volatility. All accounting ratios are winsorized at 2.5% and 97.5%.

Panel A. Momentum returns conditional on market states

	All, N=552				Up states, N=442				Down states, N=110			
Quintile	Ew ret	t-stat	alpha	t-stat	Ew ret	t-stat	alpha	t-stat	Ew ret	t-stat	alpha	t-stat
Loser	0.81%	2.85	-0.47%	-4.29	0.60%	2.14	-0.60%	-5.24	1.69%	1.90	0.08%	0.31
2	1.12%	5.04	-0.05%	-0.83	1.02%	4.58	-0.14%	-1.90	1.53%	2.29	0.20%	1.63
3	1.23%	5.91	0.09%	1.81	1.19%	5.57	0.04%	0.75	1.41%	2.34	0.17%	1.78
4	1.33%	6.20	0.21%	4.41	1.31%	5.86	0.19%	3.69	1.38%	2.36	0.18%	1.59
Winner	1.57%	5.81	0.44%	5.90	1.63%	5.54	0.54%	6.83	1.30%	1.98	0.01%	0.08
W-L	0.75%	4.56	0.90%	5.51	1.04%	6.01	1.14%	6.67	-0.39%	-0.90	-0.07%	-0.17

Panel B. Characteristics in up vs. down states

	Up states				Down states			
Variable	Mean	Q1	Median	Q3	Mean	Q1	Median	Q3
mivol	0.013	0.004	0.008	0.016	0.017	0.006	0.011	0.021
ln(M/B)	0.528	-0.012	0.456	0.985	0.413	-0.142	0.363	0.910
p6ret	12.00%	-8.13%	6.61%	24.24%	11.95%	-11.35%	6.00%	25.56%
p36_7ret	73.94%	1.45%	40.79%	98.46%	18.57%	-34.43%	-2.87%	39.56%
Sales growth	13.26%	2.86%	10.79%	21.16%	9.83%	-0.45%	8.93%	19.39%
Roa	4.41%	1.29%	4.65%	8.28%	3.18%	0.89%	3.54%	7.22%
Roe	9.67%	6.72%	11.79%	16.46%	6.66%	4.21%	9.94%	14.89%
Investment	13.12%	3.43%	9.11%	17.46%	10.52%	2.50%	6.29%	14.73%
p(M/B(t),M/B(t-1))	0.85				0.82			
p(mivol(t), mivol(t-1))	0.92				0.91			

Table 1.2 Momentum returns based on market-to-book ratio(J=6, K=6)

This table presents the average monthly abnormal returns from momentum portfolio strategies based on past returns and market-to-book ratio for the sample period from January 1965 to December 2010. A down state is the one which past 36 month value-weighted market return prior to the holding period falls into the bottom 20% of all months. The remaining 80% is defined as up states. Each month, stocks are independently sorted into quintiles based on market-to-book and past returns. Jegadeesh and Titman (1993) calendar-time strategies (J, K) = (6, 6) are implemented to obtain the time-series of equal-weighted monthly returns. The abnormal returns are the intercepts obtained from time-series regressions of equal-weighted returns on Fama and French (1993) three factors. t-statistics are presented in parentheses.

Panel A. Up state alphas (%), N=442 months

momentum	Market-to-book					G-V
	value	2	3	4	growth	
Loser	-0.37%	-0.41%	-0.44%	-0.55%	-0.94%	-0.57%
	(-3.10)	(-3.60)	(-3.88)	(-4.72)	(-6.64)	(-4.57)
2	0.08%	-0.04%	-0.13%	-0.24%	-0.37%	-0.45%
	(1.09)	(-0.51)	(-1.61)	(-2.75)	(-4.11)	(-5.68)
3	0.24%	0.08%	0.04%	-0.08%	-0.10%	-0.34%
	(3.66)	(1.23)	(0.58)	(-1.08)	(-1.28)	(-4.44)
4	0.30%	0.19%	0.14%	0.12%	0.12%	-0.19%
	(4.74)	(3.18)	(2.16)	(1.82)	(1.68)	(-2.49)
Winner	0.46%	0.55%	0.52%	0.55%	0.54%	0.08%
	(5.09)	(5.82)	(5.53)	(5.94)	(5.13)	(0.71)
W-L	0.83%	0.97%	0.96%	1.10%	1.48%	0.65%
	(4.90)	(5.45)	(5.65)	(6.37)	(7.49)	(4.08)

Panel B. Down state alphas (%), N=110 months

momgrp	Market-to-book					G-V
	value	2	3	4	growth	
Loser	-0.14%	0.11%	0.15%	0.15%	-0.06%	0.09%
	(-0.50)	(0.39)	(0.51)	(0.52)	(-0.20)	(0.30)
2	0.13%	0.24%	0.35%	0.32%	-0.08%	-0.21%
	(0.71)	(1.38)	(2.19)	(2.30)	(-0.58)	(-1.01)
3	0.29%	0.30%	0.20%	0.09%	-0.12%	-0.41%
	(1.83)	(2.24)	(1.64)	(0.76)	(-0.96)	(-2.00)
4	0.31%	0.28%	0.16%	0.11%	-0.05%	-0.36%
	(1.87)	(1.91)	(1.18)	(0.81)	(-0.36)	(-1.83)
Winner	0.18%	-0.01%	-0.18%	0.03%	-0.12%	-0.30%
	(0.84)	(-0.05)	(-1.01)	(0.18)	(-0.49)	(-1.34)
W-L	0.33%	-0.12%	-0.33%	-0.12%	-0.06%	-0.38%
	(0.78)	(-0.28)	(-0.81)	(-0.29)	(-0.14)	(-1.28)

Table 1.3 Momentum returns based on idiosyncratic volatility

This table presents the average monthly abnormal returns from momentum portfolio strategies based on past returns and idiosyncratic volatility for the sample period from January 1965 to December 2010. A down state is the one which past 36 month value-weighted market return prior to the holding period falls into the bottom 20% of all months. The remaining 80% is defined as up states. Each month, stocks are independently sorted into quintiles based on idiosyncratic volatility and past returns. Jegadeesh and Titman (1993) calendar-time strategies (J, K) = (6, 6) are implemented to obtain the time-series of equal-weighted monthly returns. The abnormal returns are the intercepts obtained from time-series regressions of equal-weighted returns on Fama and French (1993) three factors. t-statistics are presented in parentheses.

Panel A. Up state alphas (%), N=442 months

momentum	Idiosyncratic Volatility					H-L
	Low	2	3	4	High	
Loser	-0.22%	-0.42%	-0.51%	-0.58%	-0.91%	-0.69%
	(-1.89)	(-3.97)	(-4.66)	(-5.08)	(-6.27)	(-4.35)
2	-0.04%	-0.06%	-0.15%	-0.13%	-0.37%	-0.33%
	(-0.47)	(-0.72)	(-1.86)	(-1.58)	(-3.62)	(-2.47)
3	0.05%	0.09%	0.12%	0.05%	-0.14%	-0.19%
	(0.63)	(1.29)	(1.58)	(0.66)	(-1.42)	(-1.43)
4	0.17%	0.23%	0.23%	0.23%	-0.02%	-0.19%
	(2.51)	(3.35)	(3.27)	(3.45)	(-0.18)	(-1.53)
Winner	0.32%	0.43%	0.52%	0.63%	0.46%	0.13%
	(3.45)	(5.13)	(6.05)	(7.46)	(4.28)	(0.91)
W-L	0.54%	0.85%	1.02%	1.21%	1.37%	0.82%
	(3.60)	(6.29)	(7.30)	(8.02)	(7.97)	(5.03)

Panel B. Down state alphas (%), N=110 months

momentum	Idiosyncratic Volatility					H-L
	Low	2	3	4	High	
Loser	0.28%	-0.02%	0.04%	0.01%	-0.10%	-0.38%
	(0.92)	(-0.11)	(0.19)	(0.04)	(-0.29)	(-0.92)
2	0.30%	0.14%	0.27%	0.14%	-0.18%	-0.49%
	(1.79)	(1.05)	(1.91)	(0.98)	(-0.86)	(-1.61)
3	0.41%	0.23%	0.09%	0.04%	-0.36%	-0.76%
	(2.52)	(1.80)	(0.74)	(0.36)	(-1.72)	(-2.47)
4	0.47%	0.29%	0.16%	-0.04%	-0.16%	-0.62%
	(2.71)	(2.01)	(1.20)	(-0.32)	(-0.83)	(-2.13)
Winner	0.45%	0.35%	0.17%	0.05%	-0.24%	-0.70%
	(2.14)	(1.79)	(0.98)	(0.27)	(-1.01)	(-2.28)
W-L	0.17%	0.38%	0.13%	0.04%	-0.14%	-0.31%
	(0.41)	(1.10)	(0.38)	(0.11)	(-0.36)	(-0.89)

Table 1.4 Momentum returns based on market-to-book and idiosyncratic volatility

This table presents the average monthly abnormal returns from momentum portfolio strategies based on past returns, market-to-book ratio, and idiosyncratic volatility in up states within the sample period from January 1965 to December 2010. A down state is the one which past 36 month value-weighted market return prior to the holding period falls into the bottom 20% of all months. The remaining 80% is defined as up states. Each month, stocks are independently sorted into terciles based on market-to-book and idiosyncratic volatility. They are also independently sorted into quartiles based past returns. Jegadeesh and Titman (1993) calendar-time strategies (J, K) = (6, 6) are implemented to obtain the time-series of equal-weighted monthly returns. The abnormal returns are the intercepts obtained from time-series regressions of equal-weighted returns on Fama and French (1993) three factors. t-statistics are presented in parentheses.

		Idiosyncratic Volatility			
Market-to-book	momentum	Low	2	High	H-L
	Loser	-0.19%	-0.36%	-0.45%	-0.26%
		(-1.80)	(-3.38)	(-3.40)	(-1.96)
Value	Winner	0.18%	0.48%	0.53%	0.35%
		(2.12)	(6.03)	(5.19)	(2.81)
	W-L	0.37%	0.84%	0.98%	0.61%
		(2.66)	(6.24)	(6.05)	(3.94)
	Loser	-0.26%	-0.40%	-0.54%	-0.28%
		(-2.45)	(-3.87)	(-4.15)	(-2.00)
2	Winner	0.19%	0.45%	0.54%	0.36%
		(2.07)	(4.92)	(4.92)	(2.63)
	W-L	0.45%	0.86%	1.08%	0.63%
		(3.35)	(6.42)	(6.34)	(4.09)
	Loser	-0.28%	-0.59%	-0.92%	-0.64%
		(-2.40)	(-4.92)	(-6.62)	(-4.08)
Growth	Winner	0.56%	0.52%	0.45%	-0.11%
		(5.55)	(5.57)	(4.34)	(-0.77)
	W-L	0.84%	1.11%	1.37%	0.53%
		(6.04)	(7.67)	(8.06)	(3.53)
	G-V	0.47%	0.27%	0.39%	
		(3.13)	(2.18)	(2.68)	
	GW-VW	0.39%	0.05%	-0.07%	
		(3.62)	0.50	(-0.68)	
	GL-VL	-0.09%	-0.22%	-0.46%	
		(-0.73)	-2.20	(-3.72)	

Table 1.5 Characteristics of momentum portfolios

This table presents mean characteristics of 36 portfolios sorted independently by market-to-book ratio, idiosyncratic volatility and past six months return. Portfolios are formed as in Table IV. Market-to-book ratio, idiosyncratic volatility, and past six months return are calculated as in Table IV. CAPX/TA is the capital expenditures divided by the total assets. (CAPX+AQC)/TA is the ratio of the sum of capital expenditures and acquisition expenses to the total assets. The time-series means of portfolio means and medians are reported for future investment proxies separately.

Panel A. M/B

		Mivol		
M/B	p6ret	Low	2	High
Value	Loser	0.91	0.88	0.87
	Winner	0.91	0.87	0.83
2	Loser	1.59	1.61	1.65
	Winner	1.58	1.59	1.63
Growth	Loser	3.73	3.83	4.82
	Winner	3.88	3.94	4.61

Panel B. mivol (%)

		Mivol		
M/B	p6ret	Low	2	High
Value	Loser	5.85	8.94	14.33
	Winner	5.96	9.01	14.83
2	Loser	5.91	8.96	14.49
	Winner	6.00	8.99	14.88
Growth	Loser	5.98	9.09	15.15
	Winner	6.03	9.09	15.63

Panel C. p6ret (%)

		Mivol		
M/B	p6ret	Low	2	High
Value	Loser	-12.80	-16.00	-18.60
	Winner	31.90	39.80	53.80
2	Loser	-12.80	-16.40	-19.70
	Winner	32.30	39.60	52.50
Growth	Loser	-13.10	-17.30	-21.50
	Winner	32.60	39.50	51.80

Panel D. No of firms

		Mivol		
M/B	p6ret	Low	2	High
Value	Loser	46.49	62.04	46.34
	Winner	47.71	68.39	83.27
2	Loser	50.70	68.21	62.61
	Winner	41.19	61.71	72.94
Growth	Loser	33.85	66.17	129.80
	Winner	29.08	53.80	108.98

Panel E. CAPX/TA (%), mean

		Mivol		
M/B	p6ret	Low	2	High
Value	Loser	4.60	4.62	4.35
	Winner	4.97	5.30	5.05
2	Loser	4.87	5.63	5.53
	Winner	5.35	6.46	6.28
Growth	Loser	6.23	6.70	6.19
	Winner	7.10	7.91	7.22

Panel F. CAPX/TA (%), median

		Mivol		
M/B	p6ret	Low	2	High
Value	Loser	3.83	3.53	3.09
	Winner	3.89	3.75	3.54
2	Loser	4.03	4.43	3.95
	Winner	4.30	5.02	4.53
Growth	Loser	5.41	5.33	4.46
	Winner	6.29	6.61	5.46

Panel G. (CAPX+ACQ)/TA (%), mean

		Mivol		
M/B	p6ret	Low	2	High
Value	Loser	5.09	5.25	4.96
	Winner	5.55	6.14	5.88
2	Loser	5.62	6.60	6.35
	Winner	6.38	7.75	7.47
Growth	Loser	7.65	7.91	7.16
	Winner	8.72	9.40	8.40

Panel H. (CAPX+ACQ)/TA (%), median

		Mivol		
M/B	p6ret	Low	2	High
Value	Loser	4.07	3.92	3.46
	Winner	4.21	4.27	4.05
2	Loser	4.46	5.12	4.54
	Winner	5.00	6.09	5.38
Growth	Loser	6.61	6.43	5.18
	Winner	7.70	8.01	6.39

Table 1.6 Cross-Sectional Regressions

This table presents estimates of slope coefficients from Fama-MacBeth (1973) cross-sectional regressions for the sample period January, 1965 to December, 2010. The dependent variable is the average monthly return of individual firms over the six months (t+1, t+6). The dependent variables include systematic risk (beta), natural logarithm of market-to-book ratio (ln(mb)), the natural logarithm of firm size (ln(size)), idiosyncratic volatility (mivol), and the cumulative return over the past six months (t-6,t-1). At the end of each month t-1, stocks are independently sorted into market-to-book and idiosyncratic volatility terciles, and past six-month quartiles. Growth and midmb are indicator variables for the top and middle tercile of the cross-sectional distribution of market-to-book ratio, respectively. Winner and Loser are indicator variables for the top 25% and the bottom 25% of the cross-sectional distribution of six month formation period returns, respectively. The table reports average coefficients excluding the bottom 20% of market states defined as in the previous tables. t-statistics (shown in paranthesis) are adjusted for heteroskedasticity and autocorrelation using Newey-West (1987).

	All firms					High Idiosyncratic Volatility					Low Idiosyncratic Volatility				
Independent variables	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Intercept	1.354	1.350	1.349	1.348	1.349	1.770	1.746	1.750	1.749	1.750	0.987	0.987	0.990	0.991	0.990
	(5.71)	(5.72)	(5.73)	(5.72)	(5.73)	(6.01)	(5.93)	(5.94)	(5.95)	(5.94)	(4.46)	(4.50)	(4.52)	(4.53)	(4.52)
beta	0.176	0.169	0.166	0.166	0.166	0.101	0.096	0.095	0.092	0.095	0.104	0.094	0.096	0.096	0.096
	(1.46)	(1.41)	(1.39)	(1.39)	(1.39)	(0.83)	(0.80)	(0.79)	(0.77)	(0.79)	(0.82)	(0.76)	(0.77)	(0.77)	(0.77)
Ln(M/B)	-0.176	-0.183	-0.160	-0.163	-0.160	-0.242	-0.252	-0.213	-0.219	-0.213	-0.112	-0.100	-0.097	-0.105	-0.097
	(-3.58)	(-3.77)	(-3.23)	(-3.28)	(-3.23)	(-4.44)	(-4.60)	(-3.71)	(-3.78)	(-3.71)	(-2.60)	(-2.31)	(-2.21)	(-2.39)	(-2.21)
Ln(size)	-0.060	-0.060	-0.060	-0.060	-0.060	-0.040	-0.041	-0.041	-0.042	-0.041	-0.051	-0.050	-0.050	-0.050	-0.050
	(-2.51)	(-2.51)	(-2.51)	(-2.53)	(-2.51)	-1.11	-1.14	-1.16	-1.17	-1.16	-2.84	-2.84	-2.84	-2.83	-2.84
mivol	-3.153	-3.002	-2.838	-2.816	-2.838	-5.196	-4.891	-4.729	-4.718	-4.729	5.087	5.031	5.009	4.951	5.009
	(-2.71)	(-2.53)	(-2.41)	(-2.38)	(-2.41)	(-6.95)	(-6.27)	(-6.05)	(-6.09)	(-6.05)	(2.53)	(2.53)	(2.51)	(2.48)	(2.51)
p6ret	0.011	0.011	0.011	0.011	0.011	0.011	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009
	(10.27)	(8.02)	(8.02)	(8.02)	(8.02)	(9.89)	(6.69)	(6.63)	(6.65)	(6.63)	(5.92)	(4.77)	(4.75)	(4.76)	(4.75)
p6ret × midmb		0.001	0.001	0.001	0.001		0.002	0.002	0.002	0.002		-0.002	-0.002	-0.002	-0.002
		(0.89)	(0.68)	(0.78)	(0.68)		(1.49)	(1.35)	(1.41)	(1.35)		(-0.86)	(-1.01)	(-0.92)	(-1.01)
p6ret × growth		0.003	-0.002	0.001			0.004	-0.003	0.002			0.004	-0.002	0.000	
		(2.23)	(-1.34)	(0.45)			(2.49)	(-1.49)	(0.95)			(2.04)	(-0.88)	(0.22)	
p6ret × growth × loser			0.011	0.008	0.009			0.017	0.012	0.013			0.008		0.006
			(5.05)	(3.92)	(4.13)			(4.72)	(3.79)	(4.13)			(2.07)		(1.59)
p6ret × growth × winner			0.004		0.002			0.006		0.002			0.010	0.007	0.007
			(2.28)		(1.10)			(1.68)		(1.20)			(3.28)	(2.40)	(2.23)
p6ret × growth × middle					-0.002					-0.003					-0.002
					(-1.34)					(-1.49)					(-0.88)
Avg. Adj. R^2(%)	6.77	6.96	7.10	7.05	7.10	3.53	3.77	3.93	3.90	3.93	7.65	7.99	8.19	8.11	8.19

Table 1.7 Event-time long horizon performance of momentum strategies based on market-to-book

This table presents the mean cumulative equally-weighted returns and Fama-French (1993) three-factor alphas from event-time momentum portfolio strategies in up states for the sample period 1965 to 2010. At the begining of each month t, stocks are independently sorted into terciles on the basis of market-to-book ratio and into quartiles on the basis of past six month returns (from t-6 to t-1). A month (month t) is skipped between formation and holding periods. A down state is the one which past 36 month value-weighted market return prior to the holding period (t-36, t-1) falls into the bottom 20% of all months. The remaining 80% is defined as up states. Equally-weighted returns and alphas are cumulated across months t+1 to t+60. Mean cumulative returns are presented for five different event-time intervals. Panel A reports the mean cumulative equally-weighted returns. Panel B reports the mean cumulative alphas. t-statistics are adjusted to heteroskedasticity and autocorrelation by Newey and West (1987).

Panel A. Cumulative raw returns

	(t+1,t+6)		(t+7,t+12)		(t+13,t+36)		(t+37, t+60)		(t+13,t+60)	
MB	est.	tstat	est.	tstat	est.	tstat	est.	tstat	est.	tstat
value	4.39%	(6.61)	1.52%	(1.95)	-1.28%	(-0.69)	-3.13%	(-1.41)	-4.40%	(-1.40)
2	4.65%	(6.07)	1.05%	(1.42)	-5.42%	(-2.51)	-1.81%	(-0.89)	-7.23%	(-2.76)
growth	6.30%	(8.11)	1.50%	(1.91)	-7.78%	(-2.98)	-3.44%	(-1.53)	-11.23%	(-3.37)
G-V	1.92%	(3.41)	-0.02%	(-0.04)	-6.51%	(-3.88)	-0.32%	(-0.16)	-6.82%	(-2.49)

Panel B. Cumulative alphas

	(t+1,t+6)		(t+7,t+12)		(t+13,t+36)		(t+37, t+60)		(t+13,t+60)	
MB	est.	tstat	est.	tstat	est.	tstat	est.	tstat	est.	tstat
value	5.09%	(8.15)	2.93%	(4.07)	1.60%	(0.97)	-1.97%	(-0.89)	-0.37%	(-0.13)
2	5.59%	(8.33)	2.47%	(3.77)	-3.11%	(-1.73)	-0.22%	(-0.11)	-3.33%	(-1.79)
growth	7.48%	(10.42)	3.03%	(4.14)	-4.39%	(-2.10)	-1.35%	(-0.69)	-5.72%	(-2.43)
G-V	2.39%	(4.12)	0.10%	(0.16)	-5.99%	(-3.82)	0.62%	(0.36)	-5.35%	(-2.16)

Table 1.8 Event-time long horizon performance of momentum strategies based on market-to-book and idiosyncratic volatility

This table presents the mean cumulative equally-weighted returns and Fama-French (1993) three-factor alphas from event-time momentum portfolio strategies in up states for the sample period 1965 to 2010. At the begining of each month t, stocks are independently sorted into terciles on the basis of market-to-book ratio and idiosyncratic volatility and into quartiles on the basis of past six month returns (from t-6 to t-1). A month (month t) is skipped between formation and holding periods. A down state is the one which past 36 month value-weighted market return prior to the holding period (t-36, t-1) falls into the bottom 20% of all months. The remaining 80% is defined as up states. Equally-weighted returns and alphas are cumulated across months t+1 to t+36. Mean cumulative returns are presented for five different event-time intervals. Panel A reports the mean cumulative equally-weighted returns. Panel B reports the mean cumulative alphas. t-statistics are adjusted to heteroskedasticity and autocorrelation by Newey and West (1987).

Panel A. Mean cumulative equally-weighted returns

	(t+1,t+6)			(t+7,t+12)			(t+13,t+36)		
	Mivol			mivol			mivol		
M/B	low	2	High	low	2	high	low	2	high
value	2.10%	4.91%	5.25%	0.34%	1.31%	1.38%	-0.41%	-0.69%	-1.21%
	(3.09)	(8.60)	(6.94)	(0.41)	(1.82)	(1.49)	(-0.20)	(-0.33)	(-0.54)
2	1.88%	4.39%	6.28%	0.54%	0.81%	1.26%	-3.44%	-3.10%	-8.66%
	(2.84)	(7.93)	(7.56)	(0.80)	(1.31)	(1.60)	(-1.50)	(-1.57)	(-3.48)
growth	4.17%	5.83%	6.95%	2.43%	2.62%	0.48%	-1.42%	-3.73%	-12.05%
	(6.04)	(8.03)	(8.88)	(3.35)	(3.06)	(0.56)	(-0.59)	(-1.27)	(-5.02)
G-V	2.06%	0.91%	1.70%	2.09%	1.31%	-0.90%	-1.00%	-3.04%	-10.85%
	(2.44)	(1.34)	(2.27)	(2.57)	(1.74)	(-1.09)	(-0.39)	(-1.44)	(-4.76)

Panel B. Mean cumulative alphas

	(t+1,t+6)			(t+7,t+12)			(t+13,t+36)		
	Mivol			mivol			mivol		
M/B	low	2	High	low	2	high	low	2	high
value	2.50%	5.56%	6.28%	1.63%	2.50%	2.87%	2.22%	2.82%	1.55%
	(3.72)	(9.92)	(8.64)	(2.12)	(3.70)	(3.40)	(1.21)	(1.44)	(0.68)
2	2.41%	5.30%	7.24%	1.31%	2.14%	2.86%	-1.91%	-0.52%	-5.03%
	(3.74)	(10.45)	(9.52)	(2.05)	(3.94)	(3.93)	(-1.03)	(-0.33)	(-2.28)
growth	5.12%	7.04%	8.17%	3.51%	4.21%	2.13%	1.74%	0.25%	-8.38%
	(7.87)	(10.79)	(10.89)	(5.32)	(5.79)	(2.56)	(0.90)	(0.12)	(-4.29)
G-V	2.64%	1.48%	1.89%	1.88%	1.71%	-0.74%	-0.48%	-2.57%	-9.93%
	(3.20)	(2.22)	(2.46)	(2.59)	(2.45)	(-0.90)	(-0.21)	(-1.44)	(-4.56)

Table 1.9 Winners vs. Losers, Growth firms with low and high idiosyncratic volatility

This table presents the mean monthly equally-weighted returns and Fama-French (1993) three-factor alphas of losers and winners from event-time momentum portfolio strategies in up states for the sample period 1965 to 2010. At the begining of each month t, stocks are independently sorted into terciles on the basis of market-to-book ratio and idiosyncratic volatility and into quartiles on the basis of past six month returns (from t-6 to t-1). A month (month t) is skipped between formation and holding periods. A down state is the one which past 36 month value-weighted market return prior to the holding period (t-36, t-1) falls into the bottom 20% of all months. The remaining 80% is defined as up states. Equally-weighted returns and alphas are cumulated across months t+1 to t+60. Mean monthly returns are presented for four different event-time intervals. Panel A reports the mean monthly equally-weighted returns. Panel B reports the mean monthly alphas. t-statistics are adjusted for heteroskedasticity and autocorrelation by Newey and West (1987) methodology.

Panel A. Growth, High Idiosyncratic volatility firms

	Losers				Winners			
	(t+1,t+6)	(t+7,t+12)	(t+13,t+24)	(t+25,t+36)	(t+1,t+6)	(t+7,t+12)	(t+13,t+24)	(t+25,t+36)
ew ret	0.24%	0.76%	1.27%	1.43%	1.40%	0.84%	0.70%	0.98%
	(0.84)	(2.38)	(3.99)	(4.29)	(4.32)	(2.61)	(2.35)	(3.24)
alpha	-0.88%	-0.47%	-0.03%	0.14%	0.48%	-0.12%	-0.40%	-0.19%
	(-9.95)	(-3.76)	(-0.18)	(0.79)	(4.37)	(-1.09)	(-3.08)	(-1.27)

Panel B. Growth, Low Idiosyncratic volatility firms

	Losers				Winners			
	(t+1,t+6)	(t+7,t+12)	(t+13,t+24)	(t+25,t+36)	(t+1,t+6)	(t+7,t+12)	(t+13,t+24)	(t+25,t+36)
ew ret	0.72%	0.76%	1.07%	1.18%	1.42%	1.17%	1.04%	1.09%
	(4.45)	(4.12)	(6.98)	(6.64)	(8.27)	(5.91)	(5.57)	(6.72)
alpha	-0.33%	-0.25%	-0.03%	0.05%	0.53%	0.34%	0.09%	0.07%
	(-3.40)	(-2.52)	(-0.34)	(0.49)	(5.36)	(3.66)	(0.96)	(0.70)

Table 1.10 Future investment and abnormal returns of growth winners

This table presents the mean monthly equally-weighted returns and Fama-French (1993) three-factor alphas of winners from event-time momentum portfolio strategies in up states for the sample period 1965 to 2010. At the begining of each month t, stocks are independently sorted into terciles on the basis of market-to-book ratio and idiosyncratic volatility and into quartiles on the basis of past six month returns (from t-6 to t-1). Within each group, stocks are further sorted into terciles based on future investments proxied by the next year capital expenditures scaled by total assets. A month (month t) is skipped between formation and holding periods. A down state is the one which past 36 month value-weighted market return prior to the holding period (t-36, t-1) falls into the bottom 20% of all months. The remaining 80% is defined as up states. Equally-weighted returns and alphas are cumulated across months t+1 to t+60. Mean monthly Fama-French three factor model abnormal returns are presented for the second year following formation (t+13,t+24).

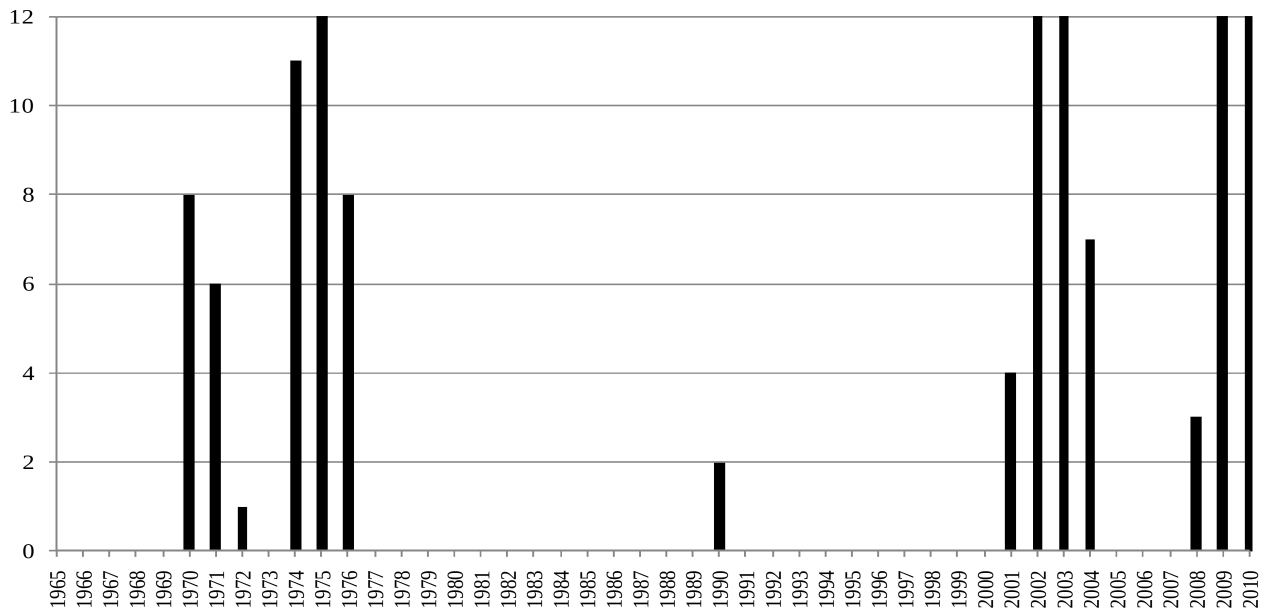
	Growth, high mivol			Growth, low mivol		
investment level	investment	abnormal returns (t-statistic)		Investment	abnormal returns (t-statistic)	
low	2.44%	-0.35%	(-2.53)	3.25%	0.07%	(0.67)
medium	5.25%	-0.29%	(-2.30)	4.92%	0.16%	(1.41)
high	13.94%	-0.58%	(-3.01)	13.15%	-0.04%	(-0.34)
H-L		-0.23%	(-1.61)		-0.11%	(-1.01)

	Value, high mivol			Value, low mivol		
investment level	investment	abnormal returns (t-statistic)		investment	abnormal returns (t-statistic)	
low	2.02%	-0.10%	(-0.32)	1.91%	0.30%	(1.85)
medium	5.10%	0.08%	(0.67)	5.04%	0.18%	(0.71)
high	8.07%	-0.11%	(-0.23)	7.93%	0.32%	(2.13)
H-L		-0.01%	(-0.05)		0.02%	(0.21)

Figure 1.1 Market states and momentum returns

Panel A plots the number of months within a given year for which the past 36-month value-weighted market return prior to the holding period falls into the bottom 20% of market states. Panel B plots the equally-weighted monthly average momentum returns for each quintile of market states. The sample period is from 1965 to 2010.Each month, stocks are sorted into quintiles based on market-to-book ratio and past returns. Momentum returns are measured by implementing calendar-time strategy with (J,K)=(6,6).

Panel A. Distribution of down states through time



Panel B. Equally-weighted momentum returns across market states

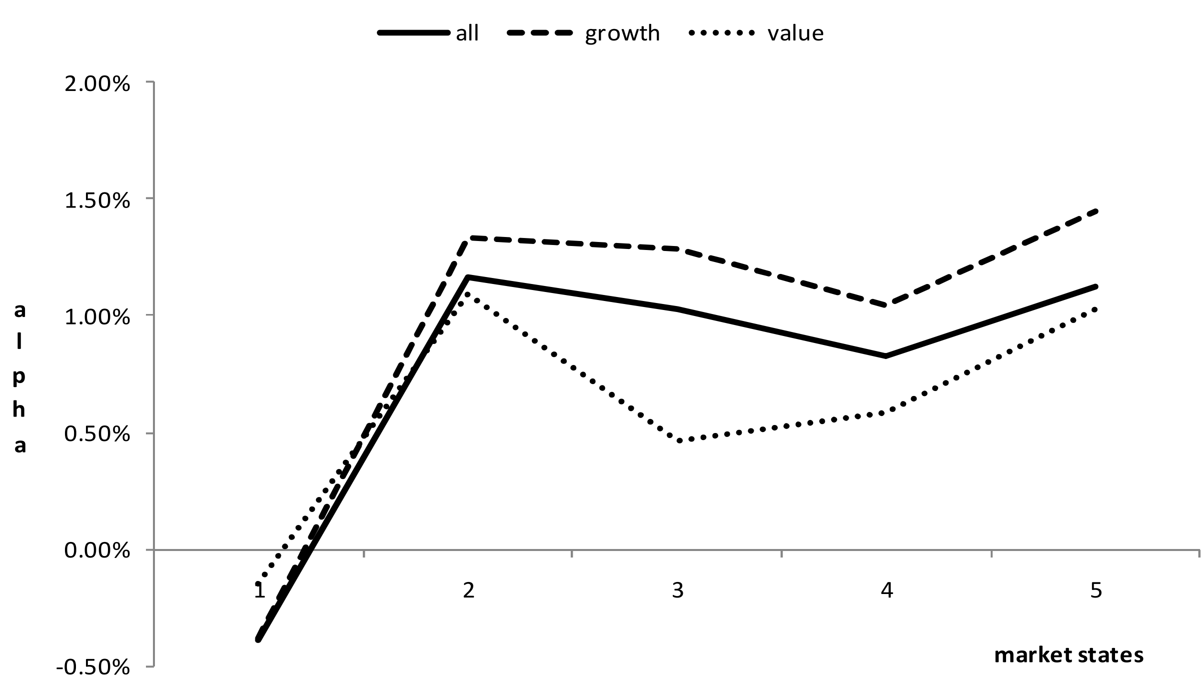
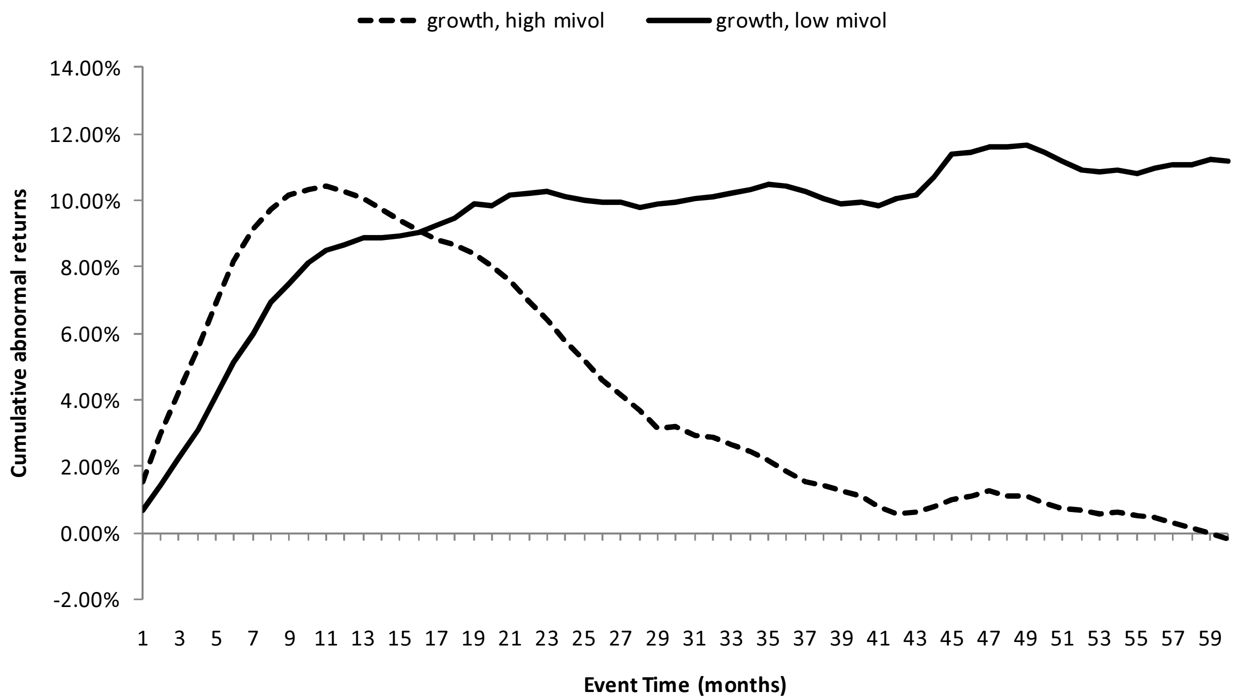


Figure 1.2 Event-time long horizon performance of momentum portfolios based on market-to-book and idiosyncratic volatility

We plot mean cumulative abnormal momentum profits over the months t+1 to t+60 for the period 1965 to 2010 by using the event-time methodology for three-way independent sorted portfolios based on past 6 month returns (t-6,t-1), market-to-book ratios and idiosyncratic volatility.

Panel A. Growth firms



Panel B. Value firms

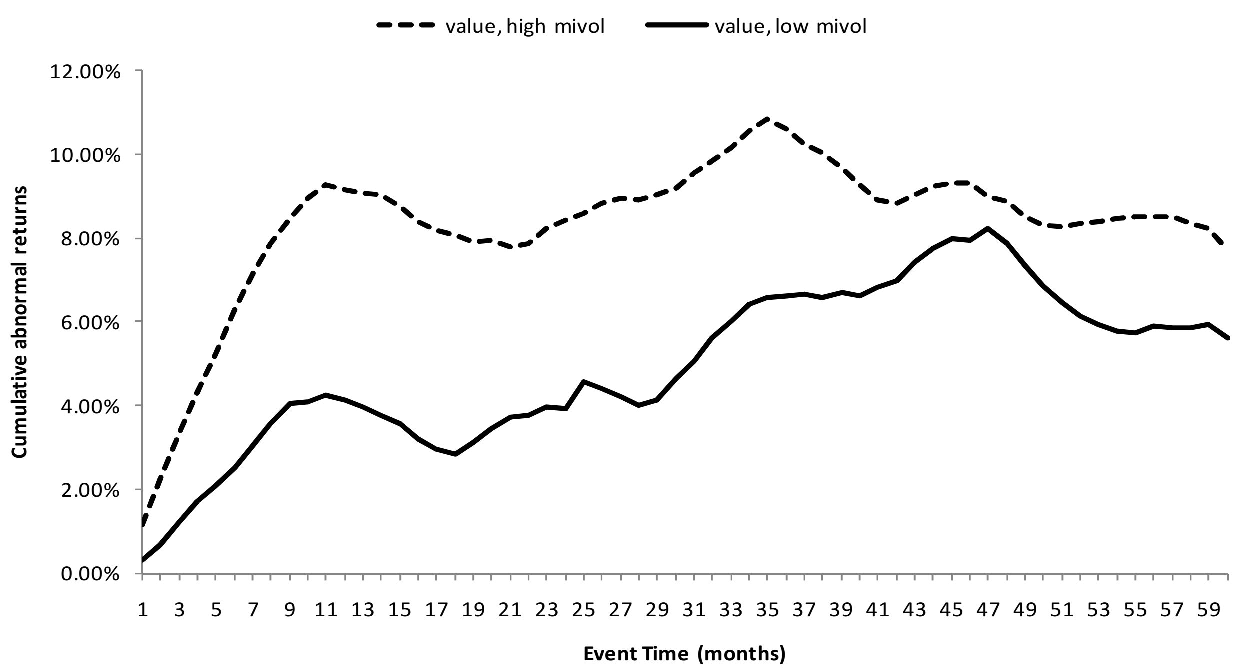
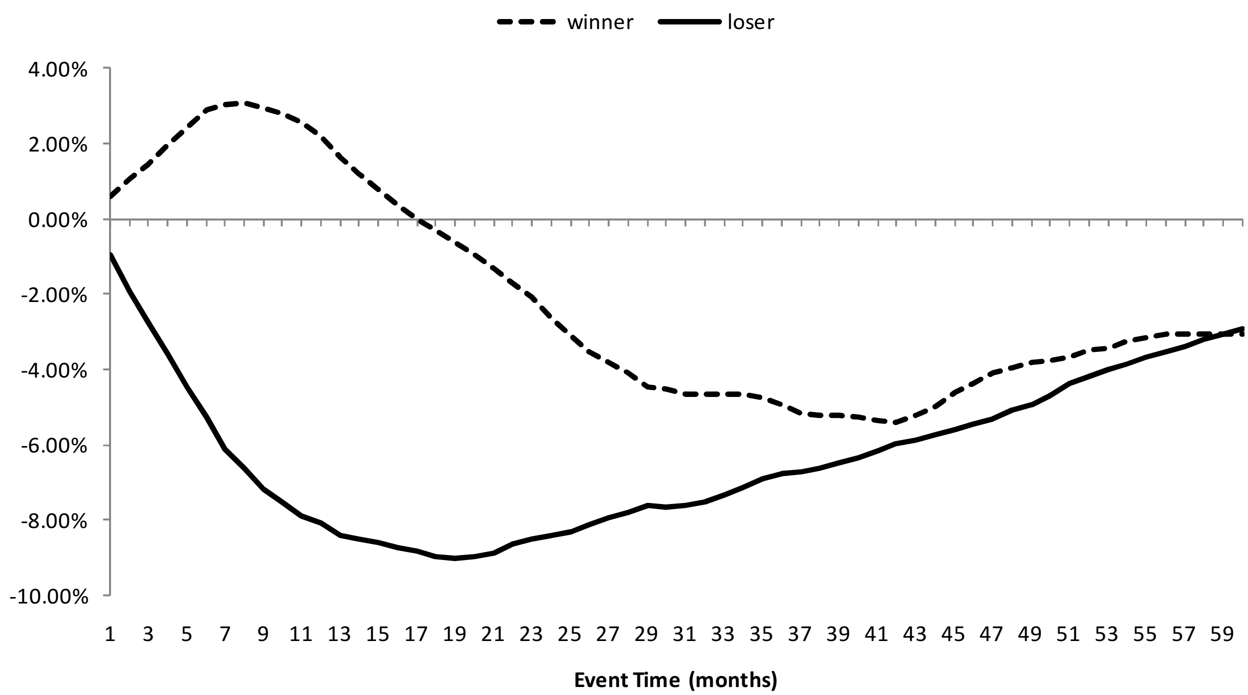


Figure 1.3 Event-time cumulative returns of winners and losers of growth firms

We plot mean cumulative abnormal returns of winners and losers over the months t+1 to t+60 for the period 1965 to 2010 by using the event-time methodology for three-way independent sorted portfolios based on past 6 monts returns (t-6,t-1), market-to-book ratio and idiosyncratic volatility.

Panel A. High Idiosyncratic Volatility



Panel B. Low Idiosyncratic Volatility

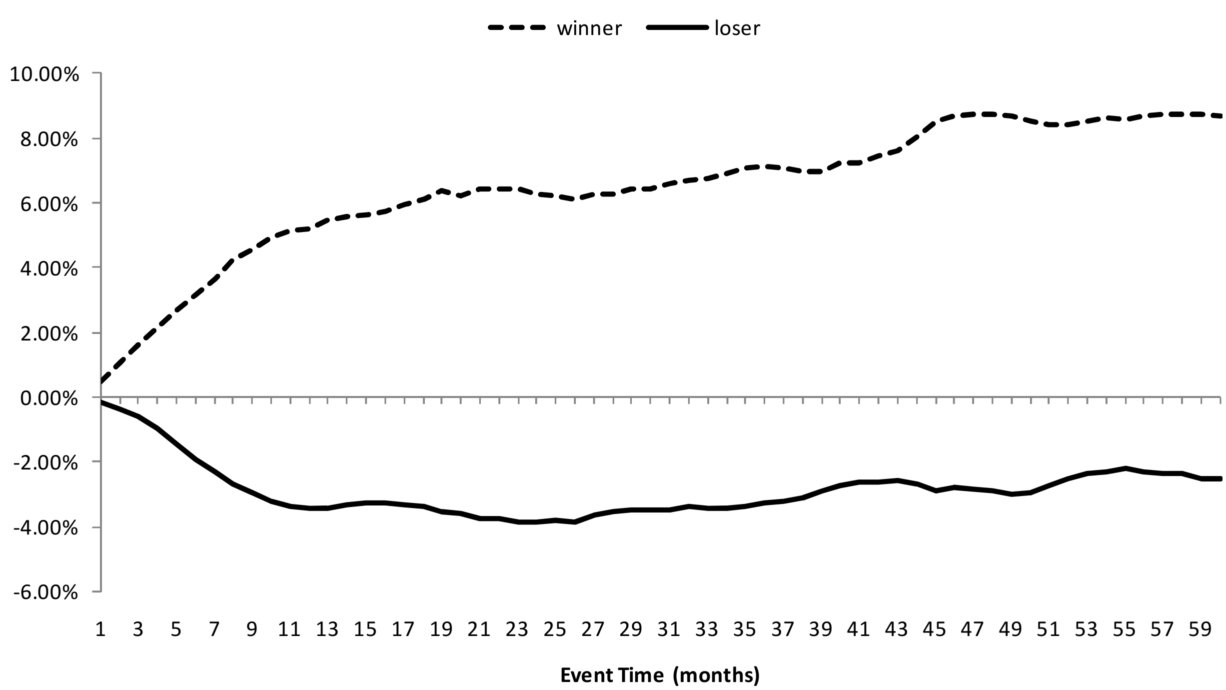
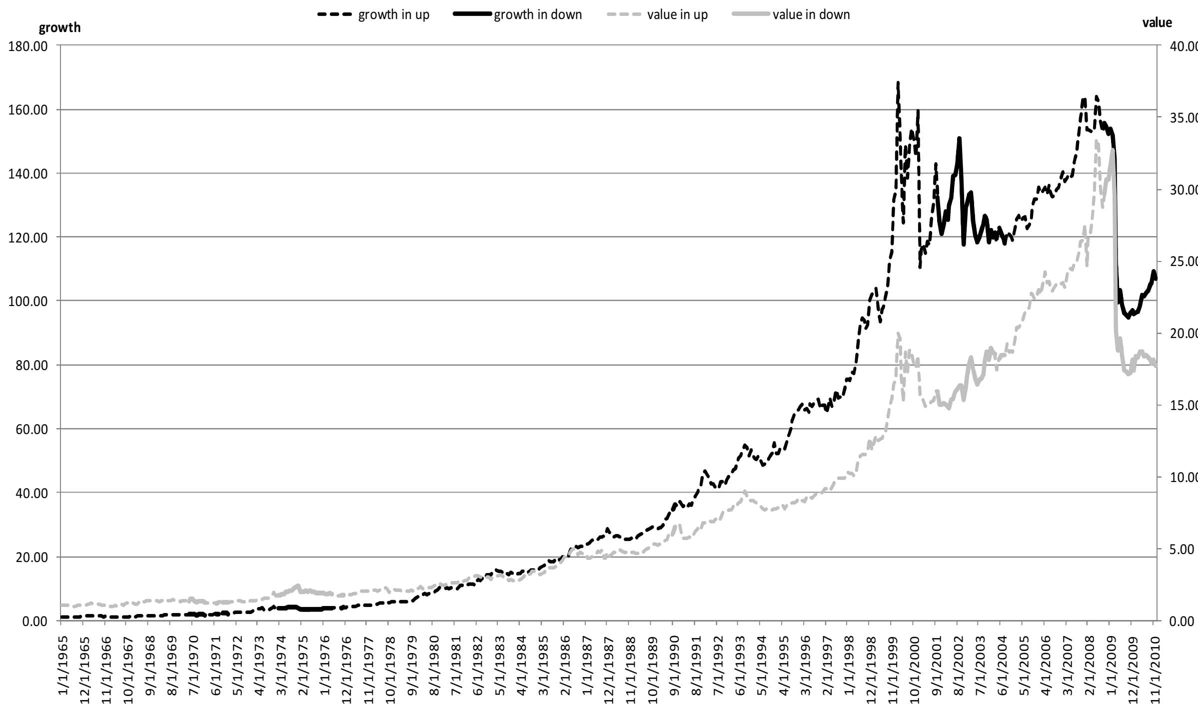


Figure 1.4 Time-series profitability of momentum strategies in value versus growth firms
We plot the value over time of $1 invested in value vs. growth momentum strategy that takes long positions in momentum strategies in growth and value stocks. The left (right) y-axis shows the values for growth (value) firms.



Chapter 2

Asset Prices When Differences of Opinion are Common Knowledge

2.1. Introduction

Conventional asset pricing models are built on the premise that investors have homogeneous expectations regarding the probability distribution of future returns. While this assumption greatly simplifies the analysis and produces useful insights, these models fail to explain a number of persistent trading patterns observed in the financial markets. For example, trading volume is far larger than can be explained solely by liquidity and portfolio rebalancing needs of investors; outstanding short-interest is generally quite high; institutional investors trade heavily for purposes of active portfolio management; and research analysts, whose stock recommendations and earnings forecasts are closely followed by investors, often report divergent expectations.[26]

While these stylized facts are commonly attributed to the heterogeneity of investors' expectations, asset pricing implications of such heterogeneity are more controversial.[27] According to asset pricing models built on the assumption that investors hold divergent expectations, asset prices reflect the weighted average of investors' beliefs regarding asset payoffs. Without market frictions, pessimistic investors' beliefs are reflected in stock prices, even if they are not holding the stock. In contrast, with market frictions that disproportionately affect the pessimistic investors (e.g., costly short-selling), pessimistic investors will be sidelined and assets prices may be inflated as hypothesized by Miller (1977), *if optimistic investors holding the stock fail to adjust their beliefs properly to account for such market frictions*. For instance, models assuming rational expectations predict unbiased prices even if short-selling is restricted, as long as rational investors take full account of market frictions and update their

[26] Differences of opinion among investors may be caused by differences in investors' information set, differences in their priors, or differences in their interpretation of information.

[27] Theoretical examinations of heterogeneous expectations and asset prices include Lintner (1969), Miller (1977), Williams (1977), Harrison and Kreps (1978), Mayshar (1983), Admati (1985), Varian (1985), Diamond and Verrecchia (1987), Biais et al. (2003), Scheinkman and Xiong (2003), Basak (2005) and Levy et al. (2006) among others.

expectations accordingly (Diamond and Verrecchia, 1987). Consequently, how heterogeneity of expectations affects asset prices depends on whether investors can impute the beliefs of sidelined investors and how they update their beliefs in response.

In this study, we investigate how investors update their beliefs on the face of heterogeneous expectations by conducting an event study of the market's reaction to revisions of analysts' dispersed earnings forecasts. A critical feature of earnings forecast dispersion as a proxy for heterogeneous expectations is that the reporting of individual forecasts by multiple analysts makes disagreements common knowledge for all market participants. This permits us to evaluate the rationality of the market's response to dispersed forecasts by ruling out structural uncertainty and limited information as alternative explanations for any potential mispricing.[28] Consequently, market's reaction to dispersed forecast revisions constitutes a special case in evaluating rationality as an acceptable representation of investor behavior. After all, if investors misprice securities when the full spectrum of opinions are common knowledge, it is highly unlikely that they will be able to price securities correctly under the more common circumstance of opaque disagreements that require extraction of information from noise prices and trading volume.

Ours is not the first study to investigate the asset pricing implications of analysts' forecast dispersion. Existing empirical evidence raises serious doubt on the view that investors capitalize differences of opinions rationally. Ackert and Athanassakos (1997), and Diether et al. (2002) document a strong negative relation between forecast dispersion and future stock returns. This overpricing of high dispersion stocks is generally attributed to an optimism bias on the part of investors holding the stock in the spirit of Miller (1977). The implication is that investors fail to update their opinions rationally upon observing dissenting forecasts and instead overweight their own overly optimistic opinions, which leads to more severe overpricing when disagreements are greater.

While such irrationality on the part of investors, along with market frictions, could cause overpricing in stocks with greater differences of opinion as envisioned by Miller (1977), whether the low returns earned by high dispersion stocks are in fact driven by this phenomenon is not a

[28] The importance of the availability of information when evaluating investor rationality is highlighted by the findings of Chae (2005), who find that while uninformed investors react properly to increased adverse selection costs prior to scheduled corporate announcements by curtailing their trading, they fail to do so around unscheduled announcements. Market makers, on the other hand, are able to modify their actions appropriately as they can extract the relevant information from their order books.

foregone conclusion. For instance, Han and Manry (2000) document that firms with high dispersion subsequently experience poor *operating* performance, which hints at an alternative driving force for the dispersion phenomenon. Importantly, the dispersion phenomenon does not naturally follow from Miller's model. Miller's framework is built on investors' uncertainty regarding the probability distribution of returns. However, the availability of analysts' divergent forecasts itself could substantially diminish uncertainty related to future earnings by making differences of opinion common knowledge. Evidence from laboratory experiments of common value auctions supports this view. Kagel and Levin (1986) find that the winner's curse problem is significantly less severe when bidders receive informative signals on another bidder's valuations. Similarly, Levin et al. (1996) show that in ascending-price auctions, which allow bidders to observe the actions of other bidders, winner's curse is less pronounced than sealed-bid auctions. The dispersion phenomenon is particularly surprising in light of these findings since the common knowledge of analysts' forecasts should substantially diminish this type of winner's curse problem.

Using the event-study methodology, we investigate whether investors ignore the dispersion in analysts' forecasts and exhibit over-optimism in their reaction to forecast revisions. Our empirical approach allows us to follow the joint evolution of earnings forecasts and stock prices over time, and investigate the genesis of the dispersion phenomenon. To assist us in our empirical analysis, we construct a simple Bayesian model of investors' revision of their expectations in response to analysts' forecasts. We first examine a baseline scenario with rational investors reacting to unbiased forecasts. Two central predictions of the model are that (i) rational investors take into account the full distribution of forecasts, and (ii) they place a smaller weight on revisions when dispersion is high. Introducing investors with biased priors produces interesting insights. According to the model, overly optimistic investors overreact to optimistic forecasts, which create a direct link between the dispersion phenomenon and the market's overreaction to forecast revisions, and motivate our event-study analysis.

Our event-study findings reveal that investors *do* take the heterogeneity in expectations into account in a manner consistent with a rational updating of beliefs when they respond to forecast revisions. The essence of our main result is captured in Figure 2.1, which reports the absolute value of the average cumulative abnormal returns observed during the three trading days surrounding earnings forecast revisions for stocks sorted by forecast dispersion. The critical observation is that the absolute announcement returns are negatively related to dispersion, which indicates that the market reaction is subdued when disagreements are greater. This result is confirmed in a multivariate setting with controls for the magnitude and the information content of the revisions, as well as several proxies for the revising analyst's visibility among investors. According to the regression results, the stock price reaction a forecast revision generates is roughly 80% larger for stocks in the lowest dispersion quintile compared to those in the highest dispersion quintile. This negative relation between the market reaction to revisions and forecast dispersion is statistically and economically very significant.

We also find evidence against the premise that investors overweight optimistic expectations when pricing assets. Controlling for the magnitude of the revision and forecast dispersion, neither optimistic revisions nor revisions by the more optimistic analysts generate a more pronounced market reaction. In fact, there is some evidence that the market discounts optimistic analysts' forecasts. In addition, pessimistic analysts' upward revisions towards the consensus forecast trigger a significantly positive market reaction, indicating that pessimistic expectations were already embedded in the market price.

If investors take account of the heterogeneity in analysts' forecasts and asset prices incorporate pessimistic expectations as implied by the event-study results, what causes the overpricing of high dispersion stocks? An extension to the Bayesian model introducing over-optimism to analysts' forecasts offers a hint. According to the model, when rational investors are endowed with the information that some analysts are over-optimistic in their forecasts but do not know precisely which ones, they perceive pessimistic forecasts to be more accurate and respond more strongly to those forecasts. Our event-study findings do not reveal such a clear asymmetric response to the forecasts of pessimistic analysts despite pervasive evidence of over-optimism in analysts' earnings forecasts.[29]

This leads us to investigate whether the overpricing of high dispersion stocks is caused by analysts' over-optimism bias as implied by the event-study findings. To address this, we employ a portfolio approach by sorting stocks based on forecast dispersion and the direction of forecast revisions. We then track the abnormal returns earned by each portfolio over time. We pay special

[29] Chan et al. (1996) document that analysts respond sluggishly to past unfavorable news. Easterwood and Nutt (1999) show that analysts underreact to negative information and Scherbina (2008) shows that some analysts withhold unfavorable information by stopping revising their forecasts. Chen and Jiang (2006) find that analysts overweight their private information if it is optimistic but underweight it if it pessimistic.

attention to two groups of stocks that experience revisions away from the consensus: (i) stocks with upward revisions by analysts whose prior forecasts were above the consensus (diverging optimists), and (ii) stocks with downward revisions by analysts whose prior forecasts were below the consensus (diverging pessimists).[30]

We find that stocks with diverging optimistic revisions *do not* subsequently earn negative abnormal returns, and the return difference between high and low dispersion portfolios is not statistically significant. Therefore, the discounting of forecast revisions in high dispersion stocks documented in our event-study analysis appears to be large enough to prevent systematic overpricing following upward revisions. Stocks with diverging pessimistic revisions, on the other hand, experience significantly negative returns following portfolio formation, especially when the forecast dispersion is high. This, then, drives the dispersion phenomenon documented by Diether et al. (2002). A multivariate analysis using Fama & MacBeth (1973) cross-sectional regressions confirms that the negative relation between stock returns and the magnitude of dispersion comes entirely from stocks that experience unfavorable revisions in the recent past.[31]

In sum, the overpricing of high dispersion stocks does not appear to be due to a categorical over-optimism bias of investors and an inability to take full account of heterogeneous expectations, but rather due to their naïveté regarding analysts' aversion to issue unfavorable forecasts. While investors' inability to take full account of analysts' biases violates the rational expectations paradigm, it is not necessarily evidence against investor rationality.[32] Both rationality and rational expectations require investors to take full account of differences of opinion that are common knowledge; our event-study findings demonstrate that they in fact do so. Correcting for analysts' resistance to issue unfavorable forecasts, on the other hand, requires a careful examination of a large enough sample of analysts forecasts and earnings announcements over a long enough period of time to make statistically significant inferences

[30] Clement and Tse (2005) find that such "bold" forecasts incorporate more private information and tend to be more informative.

[31] This is consistent with Erturk (2006), who reports a weaker cross-sectional relation between future stock returns and forecast dispersion following recent increases in the consensus forecast. He attributes the dispersion phenomenon to a "market underreaction to bad news" but does not explore the market's reaction to forecast revisions, nor the mechanisms behind the underreaction.

[32] Here we follow Brav and Heaton (2002) in distinguishing rationality from rational expectations based on investors' access to structurally relevant information. Investors may act rationally, and yet violate rational expectations, if they make optimal statistical decisions based on incomplete structural knowledge.

regarding systematic forecast errors.[33] As Brav and Heaton (2002) demonstrate, structural uncertainties of this type may cause mispricing even if investors are perfectly rational. Moreover, the trend over time in the profitability of the dispersion strategy is consistent with learning by market participants. We find that abnormal returns have declined substantially starting around 2002, which roughly coincides with the congressional hearings on analysts' incentives and the global research settlement, which generated substantial publicity regarding research analysts' conflicts of interest in the financial press as well as in academic research.

While we do not find any evidence of systematic investor over-optimism in stocks with high forecast dispersion, our results do not imply that Miller (1977) type overpricing could not be at play in other settings where heterogeneous expectations are more opaque. In fact, the mispricing of high dispersion stocks due to investors' credulity regarding analysts' incentives may itself be a manifestation of the Miller effect. If some investors fail to account for the analysts' over-optimism due to structural uncertainty, limited attention, or unfamiliarity with the phenomenon, short-sale constraints may sideline investors that are more knowledgeable, and consequently cause overpricing as envisioned by Miller (1977). The central distinguishing factor of this alternative hypothesis is that the heterogeneity is caused by differences in investors' knowledge and access to information, not over-confidence in their own expectations.

The remainder of the paper is organized as follows. In section 2.2, we motivate our empirical analysis by developing a simple model of investors' reaction to analysts' forecasts. In section 2.3, we describe the data. Section 2.4 presents the main empirical findings. And section 2.5 concludes.

2.2. A Simple Model of Investor Reaction to Analysts' Forecasts

In this section, we develop a Bayesian updating model of investor reaction to analysts' forecasts. In section 2.2.1, we investigate how a representative investor updates his earnings expectations upon observing a forecast revision by an analyst in a setting with multiple analysts with heterogeneous forecasts. In the reminder of section 2.2, we examine how investors update their beliefs regarding an analyst's precision upon observing her earnings forecast. In section 2.2.2, the investor is assumed to be over-optimistic and analysts are unbiased. In section 2.2.3,

[33] Evidence of this type of rational learning is reported by Chen et al. (2005), who find that investors put increasing weights on an analyst's forecast accuracy as they observe and learn from the analyst's track record.

the investor is unbiased but analysts' earnings forecasts are on average upward biased due to analysts' incentives.

2.2.1. The baseline scenario with rational investors and unbiased analysts

Our baseline model investigates how investors update their beliefs in response to forecast revisions by analysts. At this stage we assume that analyst forecasts are unbiased. Our primary focus is on how disagreements among analysts affect the market reaction to forecast revisions when the disagreements are common knowledge and investors are Bayesian rational.

We assume that a representative investor's prior earnings expectation is distributed normally with a mean of θ_0 and precision h_0, i.e., $N(\theta_0,1/h_0)$. The investor then observes simultaneous earnings forecasts from *N* analysts. The analysts' forecasts are random drawings from a normal distribution with mean θ_i and variance $1/h_a$ such that the precision of the signal is h_a, i.e., $s_i|x\sim N(\theta_i,1/h_a)$, where x is the actual earnings outcome.

The investor's observation of the *N* forecasts leads to a posterior expectation of

$$E(x\,|\,s) = \frac{\theta_0 h_0 + \bar{\theta} N h_a}{h_0 + N h_a}\ , \tag{1}$$

where $\bar{\theta}$ is the mean of the analysts' forecasts and $1/Nh_a$ is the variance of the analysts' earnings forecasts.

Given Eq. (1), we investigate how an investor updates his earnings expectations upon observing a forecast revision. Assuming an update of $\Delta\theta_i$ by one of the analysts, and for simplicity ignoring the resulting small change in the observed forecast dispersion, the change in the investor's posterior due to the revision is,

$$E(\Delta x\,|\,s_i) = \frac{(\Delta\theta_i/N)(Nh_a)}{h_0 + Nh_a} = \frac{\Delta\theta_i h_a}{h_0 + Nh_a}. \tag{2}$$

Thus, the investor's reaction to the revision is a function of the magnitude of the earnings revision, the precision of the investor's prior, the perceived precision of the revising analyst, and the forecast dispersion.

The magnitude of the investor's reaction per a unit change in the forecast is given by,

$$\frac{E(\Delta x\,|\,s_i)}{\Delta\theta_i} = \frac{h_a}{h_0 + Nh_a}. \tag{3}$$

Importantly, the reaction to the revision given in Eq. (3) does not include a term for the revising analyst's initial forecast relative to other analysts, indicating that the rational reaction to unbiased forecasts does not depend on the analyst's relative optimism or pessimism.

To explore the effect of forecast dispersion on the investor's reaction, we take the derivative of Eq. (3) with respect to the precision of the analysts' forecasts:

$$\frac{\partial \frac{E(\Delta x \mid s_i)}{\Delta \theta_i}}{\partial h_a} = \frac{h_0}{(h_0 + N h_a)^2}. \tag{4}$$

According to Eq. (4), the derivative of the reaction with respect to analysts' precision is positive, indicating that the reaction should be smaller when the disagreement among analysts is larger since forecast dispersion is proportional to the inverse of precision. We thus have the following proposition:

PROPOSITION 1: *If investors are rational in the sense that they capitalize heterogeneous expectations, then:*

1. *The response to revisions should be negatively related to forecast dispersion.*
2. *The market reaction should be independent of the revising analyst's relative optimism.*

For the analysis in the remainder of section II, we assume that analysts' forecasts have a private information component, which causes a cross-sectional variation in the precision of the analysts' forecasts. Investors have prior beliefs regarding analysts' precision, which is updated after observing the forecasts.

2.2.2. Over-optimistic investors

Here we adopt the framework of Jackson (2005). A stock has two potential earnings outcomes that are equally likely, with $x_H > x_L$ and $Pr(x_H) = Pr(x_L) = 0.5$. However, an over-optimistic investor over-estimates the likelihood of the good state such that $\gamma = Pr(x_H) > 0.5$. In Miller's (1977) heterogeneous expectations framework, it is precisely these over-optimistic investors that end up holding the stock while unbiased investors (as well as overly pessimistic ones) are sidelined due to market frictions.

A single analyst follows the stock and provides an earnings forecast. The analyst is one of two types; a "good" analyst who receives an informative private signal regarding the earnings or a "bad" analyst who receives random noise as a signal. The investor does not know the type of the analyst but has a prior expectation that Pr(good) = δ where $0 \leq \delta \leq 1$.

The analyst receives a private binary signal (s_H or s_L) about expected earnings with the following properties:

$$\Pr(s_H \mid x_H, \text{good}) = \Pr(s_L \mid x_L, \text{good}) = p, \tag{5a}$$

$$\Pr(s_H \mid x_L, \text{good}) = \Pr(s_L \mid x_H, \text{good}) = 1 - p, \tag{5b}$$

$$\Pr(s_H \mid x_H, \text{bad}) = \Pr(s_H \mid x_L, \text{bad}) = \Pr(s_L \mid x_H, \text{bad}) = \Pr(s_L \mid x_L, \text{bad}) = 0.5, \tag{5c}$$

where $0.5 < p < 1$.

The analyst then communicates her signal to the investor, and the investor updates his beliefs about the analyst's type based on the signal and his priors using Bayes' rule as follows:

$$\Pr(\text{good} \mid s_H) = \frac{\Pr(s_H \mid \text{good})\Pr(\text{good})}{\Pr(s_H)} = \frac{\Pr(s_H \mid \text{good})\delta}{\Pr(s_H \mid \text{good})\delta + 0.5(1-\delta)}, \tag{6a}$$

$$\Pr(\text{good} \mid s_L) = \frac{\Pr(s_L \mid \text{good})\Pr(\text{good})}{\Pr(s_L)} = \frac{\Pr(s_L \mid \text{good})\delta}{\Pr(s_L \mid \text{good})\delta + 0.5(1-\delta)}. \tag{6b}$$

According to rational investors who correctly believe that $\Pr(x_H) = \Pr(x_L) = 0.5$, analyst type is independent of the analyst's signal, i.e., $\Pr(\text{good}|s_H) = \Pr(\text{good}|s_L) = \Pr(\text{good}) = \delta$, if the forecasts are unbiased. An irrational investor with over-optimistic expectations, on the other hand, perceives relatively optimistic analysts to be more likely to be of the "good" type. This follows from

$$\Pr(\text{good} \mid s_H) = \frac{\Pr(s_H \mid \text{good})\delta}{\Pr(s_H \mid \text{good})\delta + 0.5(1-\delta)} > \delta, \tag{7}$$

since $\Pr(s_H|\text{good}) = p\gamma + (1-p)(1-\gamma) > 0.5$, for all $0.5<p<1$ and $0.5<\gamma<1$. Similarly,

$$\Pr(\text{good} \mid s_L) = \frac{\Pr(s_L \mid \text{good})\delta}{\Pr(s_L \mid \text{good})\delta + 0.5(1-\delta)} < \delta, \tag{8}$$

since $\Pr(s_L|\text{good}) = p(1-\gamma) + (1-p)\gamma < 0.5$, for all $0.5<p<1$ and $0.5<\gamma<1$.

PROPOSITION 2: *Over-optimistic investors incorrectly perceive optimistic analysts to be more accurate in their forecasts. Consequently, investors overweight optimistic forecasts and underweight pessimistic forecasts while updating their expectations.*

2.2.3. Over-optimistic analysts

In this subsection, we investigate how analysts' forecasts and the reaction to the forecasts may be influenced by analysts' incentives. To that end, we introduce an objective function for the analysts and allow analysts to report forecasts that differ from their private signal. Following

Jackson (2005), we assume that analyst face a tradeoff between building a good reputation by reporting their true private signals and collecting higher wages by reporting misleadingly optimistic forecasts and thus generating trading commissions for their brokerage firms. The assumption that analysts might be incentivized to report over-optimistic forecasts follows from the observation that favorable forecasts generate more trading than unfavorable forecasts, due in part to short-selling constraints.[34]

The analyst's objective function is

$$\max_{m} \; c.E(\text{Trade} \mid m) + k.E\big(\Pr(\text{reputation} = \text{good} \mid m)\big) \qquad (9)$$

where m is the analyst's reported forecast (m_H or m_L); E(Trade|m) is the expected amount of trading commissions generated as a consequence of the report, with $E(\text{Trade}|m_H) > E(\text{Trade}|m_L)$; Pr(good|m) is the reputation of the analyst conditional on the signal; and k captures the weight of the analyst's reputation in her objective function, with $k \in [0,\infty)$.

It follows that the analyst faces a conflict only when her private signal is s_L. When the signal is s_H, she reports m_H with certainty. When the signal is s_L, the following needs to hold for the analyst to truthfully report m_L:

$$c[E(\text{Trade} \mid m_H) - E(\text{Trade} \mid m_L)] \le k[E(\Pr(\text{good} \mid m_L)) - E(\Pr(\text{good} \mid m_H))] \qquad (10)$$

Jackson (2005) shows that the analyst will truthfully report a low signal if k exceeds a certain threshold (k^*). The investor does not know if the analyst is truthful or not, but has priors given by $\Pr(k \ge k^*) = \pi < 1$.[35]

It follows that,

$$\Pr(\text{truthful} \mid m_L) = 1 \qquad (11a)$$

$$\Pr(\text{truthful} \mid m_H) = \frac{\Pr(m_H \mid \text{truthful})\Pr(\text{truthful})}{\Pr(m_H)} = \frac{0.5\pi}{0.5\pi + (1-\pi)} = \frac{0.5\pi}{1-0.5\pi}. \qquad (11b)$$

[34] An alternative justification for the incentive to report over-optimistic forecasts is due to the fact that analysts value access to the management of the firms they cover, and this access is likely to be limited for analysts that publish reports unfavorable to the management.

[35] Jackson (2005) derives k^* as

$$k^* = \frac{c\alpha\left(\frac{\pi}{2-\pi} + q - 1\right)\left(0.25 - (p-0.5)^2\delta^2\pi^2\right)}{\pi(1+\pi)(p-0.5)(1-\delta)\delta},$$

where α is the amount of trade a unit revision in earnings expectations generates, q is the probability of facing short-selling constraints, δ is the investor's prior belief that the analyst is of "good" type, p is the probability that a "good" analyst correctly forecasts the earnings, and π is the investor's prior belief that the analyst is of truthful type.

Since $\pi < 1$, it follows that Pr(truthful|m_H) < Pr(truthful|m_L) = 1. In other words, rational investors perceive pessimistic analysts to be more truthful and pessimistic forecasts to be more accurate. The implication is that forecast revisions of pessimistic analysts lead to a larger market reaction compared to revisions by optimistic analysts.

PROPOSITION 3: *If investors know that some analysts have incentives to report deliberately over-optimistic forecasts, but don't know with certainty which forecasts are biased, they rationally overweight the forecast revisions of pessimistic analysts and underweight those of optimistic analysts.*

To test these propositions empirically, in section IV we conduct an event-study of the market reaction to forecast revisions, with a particular focus on forecast revision and the revision analyst's relative optimism.

2.3. Data

We extract daily and monthly returns from the Center for Research in Securities Prices (CRSP) database including NYSE, AMEX, and NASDAQ stocks. We use COMPUSTAT to obtain the book value of equity as the sum of book value of common equity and deferred taxes. Analysts forecasts data is from the Institutional Brokers Estimate System (I/B/E/S). We use 13(f) institutional holding data from Thomson Reuters to construct the percentage of outstanding shares held by institutional investors as an aggregate measure of institutional ownership for each firm. Stocks that are in CRSP but do not have records in 13(f) are assumed to have zero institutional ownership. Thomson Reuters records of late filings reflect the stock splits between the end of quarter and filing date. We readjust the number of shares held by institutions using CRSP daily share adjustment factors.

I/B/E/S includes U.S. Detail History and Summary History datasets, both of which are available in unadjusted and split-adjusted versions. Since our research design requires the location of each analysts forecast relative to other analysts, we use the I/B/E/S Unadjusted Detail file. We obtain individual analysts' forecasts for the forthcoming fiscal year (FY1) earnings per share (EPS) over the period 1984-2011. I/B/E/S Detail file includes individual analyst forecasts, forecast dates and revision dates. Forecast date is when an analyst initiates a forecast. Revision date is the last date on which an analyst confirms his forecast as valid and accurate. I/B/E/S enters a new record when an analyst changes his estimate and updates only the revision date when an analyst confirms his previous estimate as being unchanged.

There are two problems with the I/B/E/S Unadjusted Detail file. Occasionally, the revision date exceeds the forecast date by an unreasonably long time period (i.e., 36 months). In order to eliminate such stale forecasts, we exclude data where the time interval between the initiation of the forecast and its revision is more than 15 months.[36] And second, sometimes the revision date erroneously precedes the forecast date. In such cases we assume that the revision date and the forecast date are the same.

We assume that a forecast is valid and up-to-date during the months between the revision date and the forecast date. If an analyst has more than one valid forecast in a given month, we consider only the most recent one. After these corrections, we use individual analyst forecasts to compute the month-end standard deviation and mean values. We adjust forecasts using the cumulative share-adjustment factor from the CRSP daily stock file. Dispersion is constructed as the ratio of the standard deviation to the absolute value of the mean forecast. Following Diether, Malloy, and Scherbina (2002, DMS hereafter), we assign stocks with a mean forecast of zero to the highest dispersion group throughout our analysis.[37] Stocks with fewer than two analyst forecasts in a given month are excluded since dispersion cannot be measured in those cases.

Table 2.1 reports the summary statistics for the I/B/E/S Unadjusted Detail sample, and presents a comparison with all NYSE, AMEX and NASDAQ stocks from CRSP. We break the CRSP sample into size deciles using market capitalization breakpoints of NYSE stocks at the end of each month in each year. A firm is defined as eligible if it has a share price greater than five dollars and is followed by two or more analysts with valid earnings per share forecasts for the current fiscal year. As demonstrated in previous studies, smaller firms are less likely to be followed by security research analysts. Only 12.35% of the firms in the smallest decile are eligible for the analysis. In addition, the ratio of eligible firms increases monotonically for the larger firm deciles. Among the largest 10% of firms in the CRSP universe, 96.14% are represented in our analysis. The average number of analysts covering the smallest firms is approximately three among the smallest and 17.61 among the largest firms.

[36] Including these stale forecasts, which constitute approximately 9% of all forecasts, doesn't alter the results qualitatively.
[37] Excluding observations with a mean forecast of zero does not have a significant impact on our results.

2.4. Empirical results

We first present our results from an event study of the stock return reaction to analysts' earnings forecast revisions and evaluate how asset prices capitalize analysts' heterogeneous expectations. Then, we investigate the origins of the overpricing of stocks with high forecast dispersion by sorting dispersion portfolios into subgroups based on the direction of analysts' forecast revisions.

2.4.1. Market reaction to forecast revisions

We first conduct an event-study to examine how the market evaluates new information embedded in the earnings revisions of analysts. We pay particular attention to the relative optimism of the revising analysts and the disagreement among the analysts covering the stock. This allows us to investigate the origin of the under-performance of high dispersion stocks.

Table 2.2 presents the equal-weighted cumulative abnormal returns during the three-day window surrounding the revisions. We investigate downward and upward revisions separately. We independently sort revisions into quintiles based on the dispersion of forecasts and terciles based on the magnitude of revisions. *Dispersion* is computed as the standard deviation of forecasts divided by the absolute value of mean forecast, using all available earnings forecasts for each stock on the day before the revision date excluding the revising analyst's own forecast. The magnitude of the forecast revision is measured relative to the analyst's own prior forecast. Panel A and B report the results separately for analysts with forecasts below the consensus (pessimists) and those with forecasts above the consensus (optimists). The consensus forecast is computed as the mean of all outstanding forecasts on the day prior to the revision date.

Table 2.2 shows that the mean abnormal market return in response to forecast revisions increases with the magnitude of revisions for both optimistic and pessimistic analysts, and for both upward and downward revisions. Importantly, we observe a smaller absolute market reaction to revisions when the disagreement among analysts as captured by dispersion is larger. This subdued reaction is present in both panels and across all three revision levels. Furthermore, the reaction to revisions is closer to zero at greater dispersion levels despite the fact that the magnitude of the revisions tend to be greater for stocks with high dispersion. For example, in the low dispersion quintile, the three-day abnormal market reactions to large downward revisions by pessimistic and optimistic analysts are -7.19% and -3.77%, respectively. In contrast, in the high dispersion quintile, the corresponding abnormal returns are only -1.65% and -1.54% even though the downward revision is far larger in magnitude. These univariate results provide preliminary evidence that the divergence of analysts' expectations plays a critical role in the market's response to forecast revisions.

Next, we investigate the market reaction to forecast revisions in a multivariate setting that includes controls for the magnitude of the revision, the informativeness of the revision, and the visibility of the revising analyst. The dependent variable is the cumulative abnormal return during the three days surrounding the revision. The two main independent variables are the dispersion of all outstanding forecasts (*Dispersion*) and the change in the revising analyst's forecast scaled by the analyst's own prior forecast (*Revision*). We exclude the revising analyst's forecast when computing the forecast dispersion. We interpret the coefficient on *Revision* as the "revision response coefficient." We include *Dispersion*, as well as the control variables, as interactions with *Revision* in order to investigate how the heterogeneity of analysts' expectations and various information and visibility considerations affect the revision response coefficient.[38]

The control variables include proxies for the visibility and the informativeness of the forecast revisions. Analyst visibility is likely to affect the market's response to the revisions. For instance, each revision may have a smaller impact when a stock is covered by a large number of analysts. In addition, forecasts of analysts employed by larger brokerage houses may cause a larger trading activity. It is also possible that the immediate response may be smaller in stocks with low institutional ownership if retail investors pay less attention to analysts' forecasts and respond to revisions with a delay. To account for these potential factors, we include as control variables (i) the number of analysts with available forecasts on the day prior to revision excluding the revising analyst (*Number of analysts*); (ii) the number of analysts who have issued at least one forecast in the past year from the same brokerage house that employs the revising analyst (*Broker size*); and (iii) the percentage institutional ownership in the stock as of the most recent calendar quarter-end prior to the month of the revision (*Institutional ownership*).

At times forecasts are revised in response to public information that has already been incorporated into stock prices. Such revisions should be associated with little or no stock price reaction upon announcement. In order to capture the variation in the informativeness of

[38] An alternative approach would be to divide the announcement returns by the percentage forecast revision, and thereby include all explanatory variables linearly. This is likely to create econometric issues since small revisions would produce disproportionately large values for the dependent variable.

revisions, we include several control variables. These include an indicator that the analyst's revision is away from the prior consensus forecast—upward revisions if the analyst's most recent forecast was above the consensus and vice versa—(*Diverging dummy*); the number of days since the most recent forecast by the revising analyst (*Days since last revision*); the number of days remaining until the fiscal year-end date corresponding to the earnings forecast (*Days to fiscal-year end*); the absolute value of the cumulative stock return over the previous two weeks (*Abs(Lag Ret)*); the absolute value of the change in the consensus forecast over the previous two weeks (*Abs(Lag Rev)*); and two indicators that the analyst's revision is in the same direction as the cumulative return (*D(Lag Ret and Revision same sign)*) and the change in consensus forecast (*D(Lag Rev and Revision same sign)*). We add one to all non-indicator control variables interacted with *Revision* and then take their natural logarithm in order to account for potential skewness.[39]

In our regression specifications, the unit of observation is each individual forecast revision. Occasionally forecast revisions by different analysts for the same firm cluster in time—for instance due to a simultaneous response to an announcement—and the three-day announcement windows overlap. The resulting dependence across observations is likely to inflate the t-statistics. To overcome this problem, we compute the t-statistics after clustering observations in time for three-day windows.

The regression results in Table 2.3 confirm the univariate evidence from Table 2.2. The revision response coefficient is negatively related to forecast dispersion as evidenced by the negative and statistically highly significant slope coefficient on the interaction between dispersion and the magnitude of revision. The inclusion of the controls for visibility and informativeness does not affect the results. The coefficient on the interaction varies between -0.09 ($p<0.001$) and -0.07 ($p<0.001$) depending on the specification.[40] The economic impact of forecast dispersion on announcement returns is also highly significant. According to the

[39] Our results remain qualitatively the same when we used cumulative returns and change in consensus over the past three months.

[40] We also ran the regressions in Table III separately for upward and downward revisions, as well as revisions by optimistic and pessimistic analysts. The results are qualitatively identical. These untabulated results are available upon request.

regression estimates, the stock price reaction a forecast revision causes is 72% larger for stocks in the lowest dispersion quintile compared to stocks in the highest dispersion quintile.[41]

The slope coefficients on the control variables are also of interest. All three proxies for the visibility of the revision analyst have the expected signs. The coefficient on the interaction with the size of the brokerage house is positive and significant, indicating that the forecasts of analysts employed by brokerage houses serving a larger client base elicit a larger response. We also find evidence that the revision response coefficient is smaller if the investor base is more retail oriented. While one would think there would be more opportunities for analysts to reveal value-relevant firm-specific information when they don't have to compete with as many buy-side analysts employed by large institutional investors, the negative coefficient on the interaction with institutional ownership indicates that the response is actually subdued when institutional ownership is low, which is presumably due to retail investors' failure to react to forecasts immediately. The coefficient on the interaction with the number of analysts covering the stock is negative and highly significant, indicating that revisions are associated with a smaller reaction if the firm is covered by a larger number of analysts. This is consistent with the idea that, while the information environment may be richer for stocks with more analyst coverage, investor attention may be divided with respect to each individual forecast.[42]

With respect to the informativeness of the revisions, we find evidence of a stronger reaction when the revision is away from the consensus; when the revision follows quickly after an earlier revision by the same analyst; and when the fiscal year-end is further away. Moreover, we find that the reaction is more pronounced following a large cumulative return in either direction during the past six months, and more subdued following large changes in the consensus forecast in either direction. It appears that an earnings forecast is considered more valuable by the market following large changes in the value of the firm, especially if it is not preceded by significant revisions by other analysts. We find that the two dummy variables that capture whether the forecast revision is in the same direction as past returns and forecast revisions both

[41] According to Panel C in Table V, the average dispersion for stocks in the lowest (highest) dispersion quintile is 0.01 (0.588). Then, using the coefficient estimates from Table III, the revision response coefficient for the stocks in the lowest dispersion quintile is 0.10 (0.10-0.09[ln(1+0.01)]); whereas for the stocks in the highest dispersion quintile, it is 0.058 (0.10-0.09[ln(1+0.588)]).

[42] This finding is also consistent with the idea that the informativeness of each forecast may be less when there are a larger number of analysts competing for the same information. We do not attempt to distinguish between these two alternative explanations.

have slope coefficients that are positive and significant. The implication is that when the forecast is revised in the same direction as past returns and revisions, the stock market reaction is significantly stronger. This appears counter-intuitive at first since these revisions are more likely to be in response to past information and not revealing new information to the market. However, it is possible that these slope coefficients are capturing a cross-sectional variation in the perceived usefulness of certain analysts' forecasts. For instance, considering that forecasts tend to be dispersed, the analysts that revise their forecasts in the opposite direction of recent returns and revisions are more likely to be the ones that had large forecast errors in their initial forecasts.

Overall, the results in Table 2.3 indicate that investors place a smaller weight on a forecast revision when differences of opinion among the forecasters are greater. This finding is consistent with the idea that investors rationally capitalize heterogeneous expectations and supports Proposition 1.1. Analyst revisions may be less informative especially when some analysts revise only for the purpose of following their peers, namely herding. If investors are aware of this herding effect, they may discount such revisions. In order to take into account this effect, we exploit situations where multiple analysts make revisions on a single day in the last specification of Table 2.3 since less informative revisions due to potential herding are less likely to happen in those days. The revision variable in this last specification measures the average of the revisions measured for each analyst. We need to exclude analyst specific variables such as brokerage size, days since the last forecast and diverging dummy. All other variables are the same as before. We find that the results are similar to those in previous models such that reaction to revisions decreases with dispersion controlling for other variables.

In Table 2.4 we investigate Proposition 1.2, which states that rational investors' reaction to revisions should be independent of the relative optimism of the revising analyst. Alternatively, Proposition 2 states that over-optimistic investors overreact to the revisions of optimistic analysts, causing the stock to be overpriced due to short-selling constraints as hypothesized by Miller (1977). This, in turn, could be the mechanism behind the abnormally low returns earned by high dispersion stocks as documented by Diether et al. (2002).

The analysis in Table 2.4 is very similar to the one in Table 2.3 with one exception. We add two interaction variables that capture the impact of the revising analyst's optimism on the revision response coefficient. In specification 1, the additional variable is an indicator that the revising analyst's prior forecast was above the consensus forecast (*Optimistic analyst dummy*). In specification 2, we include a measure of where the revising analyst's prior forecast was in relation to the most optimistic forecast; namely, the highest earnings forecast minus the earnings forecast of the revising analyst prior to the revision divided by the absolute value of the consensus forecast (*Distance from highest forecast*).

According to Table 2.4, optimistic analysts do not cause a larger market response according to either of the two relative optimism measures. The first two specifications with a dummy that indicates the revisions of optimistic analysts, the slope coefficients are insignificant. In fact, in the full specification using the distance from the most optimistic forecast as a proxy for pessimism, the slope coefficient on the interaction is *positive* with a p-value less than 0.01. Consequently, investors do not appear to be exhibiting an over-optimism bias by favoring the forecasts of the more optimistic analysts, which supports Proposition 1.2 and contradicts Proposition 2.

If, as indicated by the findings in Tables 2.3 and 2.4, the market reaction upon the announcement of forecast revision is inconsistent with investor over-optimism, what causes the overpricing of high dispersion stocks? In Proposition 3 we show that rational investors that are aware of analysts' tendency to be over-optimistic with their forecasts will perceive pessimistic forecasts to be more accurate, and consequently will overweight the revisions of pessimistic analysts. The evidence in Table 2.4 for such an adjustment by investors for analysts over-optimism bias is mixed despite a large body of evidence documenting a strong optimism bias in analysts' earnings forecasts and recommendations. It is possible, then, that an inadequate adjustment by investors for analysts' biases may be behind the initial overpricing and subsequent under-performance of high dispersion stocks. The purpose of the next sub-section is to explore this possibility using a portfolio approach in the spirit of Diether et al. (2002).

2.4.2. Forecast revisions and the profitability of the dispersion strategy

In this section, we follow Diether et al.'s (2002) portfolio approach. We first replicate their size and dispersion sorted trading portfolio strategies by extending their sample period from February 1984 to December 2011 to confirm the dispersion phenomenon in the most recent sample period, and to establish a benchmark for the analysis that follows. Each month, we sort stocks sequentially into quintiles based on previous month's market capitalization and forecast dispersion. We then calculate an equally weighed return for each of the 25 portfolios, link the returns over time for each portfolio, and run time-series regressions of the portfolio excess returns on the Fama and French (1993) three-factors to estimate the abnormal returns.

The mean returns, the estimated alphas (α_i) from the Fama-French three-factor model, and the mean dispersion for each of the 25 portfolios are reported in Table 2.5. The last row in Panel A shows the average monthly raw return to the trading strategy of buying stocks in the lowest dispersion portfolio and selling stocks in the highest dispersion portfolio within each size quintile. The last row in Panel B reports the estimated alpha and the Newey-West (1987) adjusted t-statistic for the same strategy. The results in Table 2.5 are in line with the findings of DMS (2002). The difference in the average monthly excess returns and alphas of the lowest and the highest dispersion quintiles is statistically significant within the smallest three size quintiles. Among the smallest firms, the trading strategy provides a monthly abnormal return of 1.10%. The profitability of the dispersion strategy decreases with firm size: the average monthly return differential is 1.03%, 0.64%, 0.345%, and 0.37% for the second, third, fourth, and largest size quintiles, respectively. Finally, according to Panel C, the average dispersion level decreases with firm size, indicating that analysts are more likely to agree on the future earnings of larger firms. The average level of dispersion for the highest dispersion group in the small firms is 0.943, which drops to 0.309 for the largest market capitalization firms.

Next, we investigate whether the dispersion phenomenon is due to investors' over-optimism as stated in Proposition 2, due to their failure to take full account of analysts' over-optimism in violation of Proposition 3, or possibly both. To that end, we sort stocks into sub-groups based on the optimism of the revising analysts relative to the consensus forecast. Within these groups, we pay particular attention to stocks that have experienced an increase in the forecast dispersion during the previous month, either due to already optimistic analysts' further deviation from the consensus (diverging optimists) or due to pessimistic analysts' deviation from the consensus (diverging pessimists). We include a stock in the diverging optimist group if analysts with forecasts above the consensus in the previous month revise their forecasts further up while those below the consensus revise their forecasts down or make no revisions. We include a stock in the diverging pessimists group if analysts with forecasts below the consensus in the previous month revise their forecasts further down while those above the consensus revise their forecasts up or make no revisions.[43]

This separation permits us to investigate the driving force behind the dispersion phenomenon. On the one hand, if over-optimism of investors in the spirit of Miller (1977) is the primary underlying mechanism that drives the low subsequent returns earned by high dispersion stocks, we should find significant differences between the low- and high- dispersion stocks within the subgroup of stocks with analysts that exhibit diverging optimism. On the other hand, if lower subsequent returns are primarily due to investors' naïveté regarding analysts' over-optimism bias, then we expect the underperformance of high dispersion stocks to be particularly prominent when dispersion increases as a result of downward revisions by pessimistic analysts that are not matched by the optimistic analysts.

Table 2.6 reports the Fama-French three-factor alphas and t-statistics of portfolios sorted by size and dispersion within the subgroups mentioned above. The average number of firms in each portfolio drops significantly in this analysis due to our double-sorting procedure and the exclusion of stocks that do not experience an increase in dispersion. Therefore, we use three-by-three size-dispersion sorted portfolios to ensure that there are a sufficient number of firms in each portfolio.[44] In Panel A, which reports the abnormal returns to the dispersion strategy in the diverging optimists group, we observe two key findings. First, looking at the last column with the full sample results, none of the dispersion portfolios earn negative subsequent abnormal returns, indicating that stocks with increasing dispersion due to optimistic revisions do not subsequently experience abnormally low returns. Second, the dispersion strategy based on the differences between the low- and high-dispersion portfolios is not profitable. The mean abnormal return earned by a zero-cost strategy of buying low and selling high dispersion stocks is 0.18% (t=0.79). The returns earned by the dispersion strategy are positive and reasonably large only for the stocks in the middle size group, and even then they are only marginally statistically significant (p-value = 0.049).

In Panel B, we explore the profitability of the dispersion strategy among stocks that experienced downward revisions by pessimistic analysts in the prior month. In contrast to Panel

[43] There is some overlap between the two sub-groups due to the rare occasion when optimistic analysts revise their forecasts upward while pessimistic analysts revise downward. These observations constitute roughly 6% of the sample. Excluding these instances from the two sub-groups in this analysis does not alter our results.

[44] In unreported results, we find that the original dispersion phenomenon remains significant in this revised three-by-three portfolio sorting approach.

A, the dispersion strategy is significantly profitable in this group, especially among small and mid-size stocks. The average abnormal return difference between the low- and high-dispersion stocks is 72 basis points per month with a t-statistic of 3.20. Moreover, looking at the last column, we see that these stocks earn statistically significantly low future returns regardless of the level of dispersion. The mean abnormal return of low and high dispersion stocks is -0.31% (t=-2.43) and -1.03% (t=-4.78) per month, respectively. These results in Panel B, along with our finding reported in Panel A that the dispersion strategy is not profitable when the increase in dispersion is fueled by optimistic forecasts, indicate that the dispersion phenomenon is primarily due to the investors' failure to capitalize the negative information embedded in analysts' downward revisions to a full extent. This conclusion receives further support in Panel C, where we explore the profitability of the dispersion strategy among stocks with *declining* dispersion due to downward revisions of optimistic analysts (converging optimists). The average abnormal return difference between the low- and high-dispersion stocks is 63 basis points with a t-statistic of 3.95.

In Figure 2.2, we investigate the persistence of abnormal returns documented in Table 2.6 during the six months following portfolio formation. It is possible, for instance, that stocks with diverging optimists may experience abnormally low returns with a delay. To that end, we plot the abnormal returns earned by stocks in the highest dispersion quintile during the month of portfolio formation and the subsequent six months. Figure 2.2 shows that high dispersion stocks with downward forecast revisions by pessimistic analysts continue to under-perform for the next six months, with abnormal returns statistically significantly different from zero during the first four months. In contrast, stocks with an increasing dispersion due to upward revisions by optimistic analysts do not earn abnormal returns at any point during the next six months following portfolio formation. In other words, the results presented in Table 2.6 are not reversed over time.

The abnormal return findings using the portfolio strategy supplement our earlier event-study findings. The subdued reaction to forecast revisions when dispersion is high as documented in Table 2.3 appears to be sufficient to prevent systematic overpricing when the revisions are driven by an optimistic sentiment. This discounting of revisions on the face of large disagreements backfires when the revisions are downwards however, as indicated by the abnormally low returns subsequent to downward forecast revisions. Together, these results raise the possibility that while high dispersion following upward revisions may indeed proxy for large differences of opinion among analysts—evidently correctly interpreted and capitalized by investors—, high dispersion following downward revisions appears to be a manifestation of the analysts' over-optimism bias. This is consistent with the Chan et al. (1996), Easterwood and Nutt (1999) and Scherbina (2008) who document that security analysts' forecasts exhibit sluggishness to unfavorable news in particular.

This interpretation receives further support in Figure 2.3, which plots the percentage change in the consensus forecast during the five months surrounding portfolio formation for groups of stocks categorized by dispersion and size. We observe that high dispersion stocks have experienced large downward revisions during the two months prior to portfolio formation. In contrast, low dispersion stocks have average past revisions close to zero. Moreover, high dispersion stocks continue to experience downward revisions *following* portfolio formation. This asymmetry between low and high dispersion stocks lends support to the view that stale forecasts that increase dispersion are more prevalent around unfavorable news. If investors are unaware of this negative relation between high dispersion and future forecast revisions, a response that is rational from a differences-of-opinion perspective is likely to cause the overpricing of high dispersion stocks.

2.4.3. Dispersion strategy in the cross-section and forecast revisions

Next, we investigate whether the relation between the profitability of the dispersion strategy and the direction of forecast revisions documented in the previous sub-section using the time-series analysis is also present in the cross-section. To that end, we run monthly Fama and MacBeth (1973) cross-sectional regressions of stock returns on firm characteristics and several proxies related to forecast revisions. Firm characteristics include the stock's beta, size (*Ln(size)*), book-to-market ratio (ln(B/M)), past six month returns excluding the most recent month (*Lag Ret*), and the dispersion in analysts' forecasts (*Dispersion*).[45] In addition, we include four dummy variables related to the direction of forecast revisions as interactions with *Dispersion*. The diverging optimists dummy (*D(Opt_Div)*) equals one if optimistic analysts on average revised their forecasts upward during the prior month, and zero otherwise. The converging optimist

[45] In unreported tests, we include lagged idiosyncratic volatility, expected idiosyncratic volatility estimated using the EGARCH model as in Fu (2009), the number of analysts, lagged turnover, and the coefficient of variation of turnover as additional explanatory variables. The results are qualitatively identical.

dummy (*D(Opt_Con)*) equals one if optimistic analysts on average revised their forecasts downward during the prior month, and zero otherwise. The diverging pessimists dummy (*D(Pes_Div)*) equals one if pessimistic analysts on average revised their forecasts downward during the prior month, and zero otherwise. The last dummy variable, the decreasing consensus dummy (*D(Con_Down)*) equals one if the mean estimate of all analysts covering the stock decreased during the prior month, and zero otherwise. The coefficients are estimated as the time-series mean of the slope coefficients from each monthly regression. The t-statistics are adjusted using the Newey-West (1987) methodology up to six lags.

Table 2.7 presents the average slopes and t-statistics for five different specifications. Specification 1 examines the effects of beta, firm size, book-to-market, lagged returns, and forecast dispersion. Confirming Diether et al.'s (2002) findings, returns are significantly negatively related to forecast dispersion in the cross-section. In specifications 2 to 5, we include the interaction variables as explanatory variables one by one. In specification 2, the coefficient on the interaction of *Dispersion* with *D(Opt_Div)* is 1.28 with a t-statistic of 2.47, which indicates that the negative relation between dispersion and future returns documented in Specification 1 is not present among stocks that experienced an upward revision by optimistic analysts since the sum of the two dispersion coefficients is larger than zero. Specifications 3 and 4 confirm that the dispersion phenomenon is particularly strong among stocks that experience downward revisions by both optimistic and pessimistic analysts, respectively. The slope coefficient is -0.37 with a t-statistic of -2.07 for the interaction with *D(Opt_Con)*, and -0.81 with a t-statistic of -2.62 for the interaction with *D(Pes_Div)*. Finally, in specification 5 we include an interaction between *Dispersion* and an indicator for a decrease in the consensus forecast in the prior month. Importantly, the coefficient on dispersion becomes statistically insignificant, confirming that the dispersion phenomenon is almost entirely driven by downward revisions.

2.4.3. Profitability of the dispersion strategy over time

Overall, the empirical evidence from the market's reaction to forecast revisions, as well as the role of forecast revisions in the profitability of the dispersion strategy in both time-series and the cross-section indicate that the abnormally low returns earned by high dispersion stocks are not due to investors' failure to take full account of the heterogeneity of expectations. Instead, our findings implicate investors' credulity regarding analysts' over-optimism in their forecasts as a primary cause of the dispersion phenomenon. Such failure on the part of investors to fully account for analysts' misaligned incentives is potentially consistent with "rational structural uncertainty" theories. Brav and Heaton (2002) propose that unavailability of sufficient information or the difficulty of processing available information may cause mispricings even if investors are rational in the sense that they do not exhibit any behavioral biases.

An important implication of the "rational structural uncertainty" theories is that such mispricings should diminish over time and eventually disappear as more information becomes available. Consequently, rational investors should learn about analysts' over-optimism and calibrate their beliefs accordingly if structural uncertainty is a central force behind the dispersion phenomenon. In Figure 2.4, we plot the value over time of $1 invested in the dispersion strategy that takes a long position in stocks in the lowest dispersion quintile and a short position in the highest dispersion quintile at the beginning of January 1984. For presentation purposes, the y-axis is in logarithmic scale. We report the profitability of the dispersion strategy both for the full sample, and separately for the smallest 20% of stocks which has been the size group with the highest dispersion returns as demonstrated in Table 2.5.

As can be seen in Figure 2.4, the dispersion strategy has been very profitable over the full sample period of 1984 to 2011, particularly for small stocks. However, the profitability appears to have declined substantially later in the sample period. While explaining the time-series variation in the profitability of the dispersion strategy is beyond the scope of this study, the sharp decrease in profitability since approximately late 2002 roughly coincides with the wide-spread publicity research analysts' conflicts of interested received in the financial press as well as in academic research. This was the period that saw Congressional hearings on analysts' incentives in the summer of 2001, Merrill Lynch's $100 million settlement with the state of New York in May 2002 to make changes in the compensation of its analysts, the introduction of new regulations for sell-side analysts in the summer of 2002, and the $1.4 billion "global research settlement" announced in December 2002 to "resolve issues of conflict of interest" and "bolster the integrity of equity research" (Boni and Womack, 2003).

2.5. Conclusion

We examine how investors capitalize difference of opinion in the special case of common knowledge of disagreements. We conduct an empirical analysis of the market's reaction to analysts' earnings forecast revisions with a particular focus on forecast dispersion and the relative optimism of the revising analyst. The fact that the divergent expectations of analysts are readily observable permits investors to capitalize heterogeneous expectations without having to interpret information embedded in prices and trading volume. In addition, in this setting we can evaluate the rationality of the market’s response by ruling out structural uncertainty and limited information as alternative explanations for any potential mispricing. In that sense, market’s reaction to dispersed forecast revisions constitutes an important special case in evaluating rationality as an acceptable representation of investor behavior.

Ackert and Athanassakos (1997) and Diether et al. (2002) document a surprising negative relation between earnings forecast dispersion and subsequent stock returns. This finding has generally been interpreted as evidence of over-optimism on the part of investors facing large differences of opinion in the spirit of Miller (1977). We build a simple Bayesian model which reveals that over-optimistic investors are likely to overreact to the revisions of analysts with optimistic forecasts, creating a causal link between investors' reaction to forecast revisions and the dispersion phenomenon. We test the implications of the model using an event study of the market's reaction to forecast revisions. Our findings are inconsistent with the investor over-optimism hypothesis. Investors appear to take full account of heterogeneous expectations by reacting less to revisions when the forecast dispersion is large. Moreover, they do not appear to overweight forecasts by optimistic analysts.

However, our event-study analysis reveals a surprising symmetric reaction to optimistic and pessimistic forecasts. An extension of the Bayesian model with rational investors reacting to biased analysts with incentives to report over-optimistic forecasts reveals that rational investors should perceive pessimistic analysts to be more accurate and therefore put a larger weight on pessimistic forecasts. The fact that such an asymmetry is not observed in the event-study analysis raises the possibility that the overpricing of high dispersion stocks is driven by investors’ failure to fully account for analysts’ incentives to report overly optimistic forecasts.

A portfolio analysis in the spirit of Diether et al. (2002) confirms this investor-naïveté hypothesis. We find that high dispersion stocks earn abnormally low returns only following downward forecast revisions. When dispersion increases due to upward revisions by already optimistic analysts, which is when the consequences of an over-optimism bias could be expected to be the most severe, high dispersion stocks do not earn abnormally low returns. This asymmetry in the dispersion phenomenon is confirmed using the Fama and MacBeth (1973) cross-sectional regressions.

Our empirical results provide an alternative explanation for the overpricing of stocks with large forecast dispersion. We find that investors successfully account for heterogeneous expectations when those expectations are easily observed, but fail to account for analysts' incentives to report misleading forecasts. Our findings are consistent with the idea that investors are not categorically irrational but they may form biased beliefs when information is insufficient or imprecise (Brav and Heaton, 2002). An important policy implication of our findings is that more publicity regarding analysts' incentives and their track records could lead to a substantial reduction in the overpricing of high dispersion stocks.

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Table 2.1 Summary statistics

This table compares eligible firms in I/B/E/S detail unadjusted dataset with all NYSE, NASDAQ and AMEX firms in CRSP dataset. A stock is included in our analyst data if it has two or more analyst estimates for the current fiscal year earnings per share estimate at the end of a given month. All NYSE, NASDAQ and AMEX firms are allocated to deciles determined using NYSE size breakpoints. The right hand side of each panel shows the percentage of eligible firms for our analysis, the mean size (in millions dollar values) and average number of analysts with earnings per share estimates for the current fiscal year. The sample period is January 1984 to December 2011.

Summary statistics for the full sample period categorized by size						
	All CRSP stocks			I/B/E/S detail file		
NYSE size deciles	# of firms	Mean size (millions)	% of firms in I/B/E/S	# of firms	Mean size (millions)	# of analysts
1	2841	45.34	12.35	351	75.09	2.99
2	757	185.16	45.92	348	188.72	3.85
3	470	336.71	59.49	279	338.89	4.64
4	358	530.82	70.28	251	533.08	5.42
5	290	807.78	78.16	227	810.27	6.31
6	238	1215.34	83.61	199	1217.23	7.37
7	212	1849.2	87.21	185	1851.27	8.77
8	196	3079.22	91.72	180	3086.74	10.73
9	178	6269.66	94.61	168	6272.22	13.37
10	166	31011.93	96.14	160	31299.23	17.61

Table 2.2 Cumulative abnormal returns around forecast revisions

This table reports the equally-weighted average cumulative abnormal return during the three-day window surrounding individual analysts' forecast revisions for the current fiscal-year end earnings. Results are reported separately for revisions of forecasts below the mean forecast (pessimistic forecasts) and those above the mean forecast (optimistic forecasts). Furthermore, revisions are sorted into quintiles based on the dispersion of forecasts and terciles based on the magnitude of the revision. *Revision* is the percentage change in the analyst's forecast. *Dispersion* is the standard deviation of the forecasts for the same firm divided by the absolute value of the mean forecast using all eligible forecasts on the day prior to the revision excluding the forecast being revised. The sample period is January 1984 to December 2011. Panel A and Panel B present revisions of pessimistic and optimistic forecasts, respectively.

Panel A. Revisions of pessimistic forecasts

EW CAR (%)

	Downward revisions			Upward revisions		
Dispersion	Small	Medium	Large	Small	Medium	Large
Low	-7.19%	-3.60%	-1.22%	0.74%	1.40%	2.00%
2	-6.11%	-1.98%	-0.90%	0.63%	1.34%	1.77%
3	-4.45%	-1.44%	-0.57%	0.48%	1.06%	1.74%
4	-2.84%	-0.95%	-0.59%	0.44%	0.72%	1.48%
High	-1.65%	-0.79%	-0.54%	0.23%	0.44%	1.18%

Revision (%)

	Downward revisions			Upward revisions		
Dispersion	Small	Medium	Large	Small	Medium	Large
Low	-19.73%	-4.60%	-1.16%	1.33%	4.24%	13.58%
2	-18.72%	-4.55%	-1.37%	1.53%	4.50%	12.97%
3	-18.32%	-4.80%	-1.49%	1.56%	4.78%	13.48%
4	-18.56%	-5.08%	-1.54%	1.57%	4.91%	16.49%
High	-27.81%	-5.36%	-1.56%	1.55%	4.95%	21.14%

Panel B. Revisions of optimistic forecasts

EW CAR (%)

	Downward revisions			Upward revisions		
Dispersion	Small	Medium	Large	Small	Medium	Large
Low	-3.77%	-1.84%	-0.82%	1.01%	1.94%	3.68%
2	-3.04%	-1.43%	-0.57%	0.79%	1.45%	2.81%
3	-2.30%	-1.16%	-0.37%	0.57%	1.13%	2.06%
4	-1.99%	-0.80%	-0.46%	0.57%	0.97%	1.80%
High	-1.54%	-0.75%	-0.57%	0.26%	0.65%	1.57%

Revision (%)

	Downward revisions			Upward revisions		
Dispersion	Small	Medium	Large	Small	Medium	Large
Low	-23.24%	-6.11%	-1.67%	0.87%	2.80%	9.41%
2	-21.34%	-6.36%	-2.03%	0.99%	2.90%	9.25%
3	-20.30%	-7.06%	-2.11%	1.01%	3.03%	9.81%
4	-23.02%	-7.38%	-2.07%	1.00%	3.11%	11.37%
High	-36.92%	-7.52%	-2.12%	1.04%	3.16%	15.91%

Table 2.3 Cumulative abnormal returns around forecast revisions and forecast dispersion

The dependent variable is the cumulative abnormal return during the 3-day window surrounding individual analysts' forecast revisions for the current fiscal-year end earnings. *Revision* is the percentage change in the analyst's forecast in Models 1 thorough 5. In Model 6, *Revision* is the average of the percentage changes in the forecasts of analysts in days where at least two analysts make revisions for a stock. All remaining explanatory variables enter the regression as interaction variables with *Revision* in order to examine how they affect the "revision response coefficient". *Dispersion* is the standard deviation of the forecasts for the same firm divided by the absolute value of the mean forecast using all eligible forecasts on the day prior to the revision excluding the forecast being revised. *Diverging dummy* is an indicator that the revised forecast is further away from the consensus forecast. *Number of analysts* is the number of analysts with available forecasts on the day prior to revision excluding the revising analyst. *Broker size* is the total number of analysts employed by the revising analyst's brokerage house. *Institutional ownership* is the fraction of the firm's shares owned by institutional investors. *Days since last revision* is the number of days since the revising analyst's previous forecast/revision. *Days to fiscal-year end* is the number of days remaining in the firm's fiscal year. *Abs(Lag Ret)* is the absolute value of the cumulative stock return over the previous 14 trading days. *Abs(Lag Rev)* is the absolute value of the change in consensus forecast over the previous 14 trading days. *D(Lag Ret and Revision same sign)* is an indicator that *Lag Ret* and the forecast revision have the same sign. *D(Lag Rev and Revision same sign)* is an indicator that *Lag Rev* and the forecast revision have the same sign. Standard errors are clustered in time for three day windows. t-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: CAR	(1)	(2)	(3)	(4)	(5)	(6)
Revision	0.07***	0.10***	0.02***	-0.04***	-0.08***	0.04***
	(44.78)	(47.12)	(2.80)	(-4.96)	(-10.91)	(2.95)
Interactions with Revision						
Ln (Dispersion)		-0.09***	-0.09***	-0.08***	-0.08***	-0.13***
		(-36.91)	(-35.72)	(-35.36)	(-32.71)	(-21.44)
Diverging dummy			0.03***	0.03***	0.03***	
			(21.39)	(21.43)	(22.15)	
Ln (Number of analysts)			-0.03***	-0.03***	-0.03***	-0.07***
			(-20.92)	(-21.13)	(-26.37)	(-35.09)
Ln (Broker size)			0.01***	0.01***	0.01***	
			(19.97)	(20.25)	(20.47)	
Ln (Institutional ownership)			0.16***	0.16***	0.16***	0.20***
			(26.73)	(27.50)	(27.49)	(17.73)
Ln (Days since last revision)			-0.002***	-0.001	-0.001	
			(-2.96)	(-1.60)	(-0.76)	
Ln (Days to fiscal-year end)			0.005***	0.005***	0.006***	0.01***
			(3.87)	(3.89)	(5.11)	(3.98)
Ln {1+Abs(Lag Ret)}				0.01	0.02**	0.01
				(0.99)	(2.13)	(0.31)
D(Lag Ret and Revision same sign)				0.10***	0.09***	0.12***
				(34.53)	(30.19)	(28.74)
Ln {1+Abs(Lag Rev)}					-0.01***	-0.07***
					(-4.73)	(-8.54)
D(Lag Rev and Revision same sign)					0.11***	0.13***
					(54.53)	(40.57)
Adj. R2(%)	3.22	3.81	4.61	6.32	8.15	12.42
# of obs.	1,550,471	1,550,471	1,550,471	1,550,471	1,550,471	235,175

Table 2.4 Cumulative abnormal returns around forecast revisions and analysts' optimism

The dependent variable is the cumulative abnormal return during the 3-day window surrounding individual analysts' forecast revisions for the current fiscal-year end earnings. *Revision* is the percentage change in the analyst's forecast. All remaining explanatory variables enter the regression as interaction variables with *Revision* in order to examine how they affect the "revision response coefficient". *Optimistic analyst dummy* is an indicator that the revising analyst's pre-revision forecast was above the consensus forecast. *Distance from highest forecast* is the difference between the highest forecast and the revising analyst's pre-revision forecast. All other variables are defined as in Table III. Standard errors are clustered in time for three-day windows. t-statistics are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: CAR	(1)	(2)	(3)	(4)
Revision	0.09***	-0.08***	0.09***	-0.08***
	(42.56)	(-10.42)	(42.84)	(-11.33)
Optimism proxies				
Revision x Optimistic analyst dummy	-0.002	-0.005		
	(-1.60)	(-1.49)		
Revision x Distance from highest forecast			0.005**	0.01***
			(2.48)	(3.05)
Controls as Interactions with Revision				
Ln (Dispersion)	-0.09***	-0.07***	-0.09***	-0.07***
	(-37.19)	(-32.37)	(-37.19)	(-23.77)
Diverging dummy	0.04***	0.03***	0.04***	0.03***
	(20.12)	(18.12)	(22.14)	(19.16)
Ln (Number of analysts)		-0.03***		-0.03***
		(-26.36)		(-26.16)
Ln (Broker size)		0.01***		0.01***
		(20.43)		(20.25)
Ln (Institutional ownership)		0.16***		0.16***
		(27.46)		(27.45)
Ln (Days since last revision)		-0.001		-0.0004
		(-0.70)		(-0.57)
Ln (Days to fiscal-year end)		0.006***		0.01***
		(5.09)		(5.15)
Ln {1+Abs(Lag Ret)}		0.02		0.02*
		(1.59)		(1.64)
D(Lag Ret and Revision same sign)		0.08***		0.08***
		(32.49)		(32.44)
Ln {1+Abs(Lag Rev)}		-0.01***		-0.01***
		(-4.73)		(-4.73)
D(Lag Rev and Revision same sign)		0.11***		0.11***
		(54.51)		(54.54)
Adj R2(%)	3.95	8.16	3.95	8.16
# of obs.	1,550,471	1,550,471	1,550,471	1,550,471

Table 2.5 Forecast dispersion and portfolio returns

Each month stocks are sorted into quintiles based on the market capitalization at the end of the previous month. Stocks in each size group are further sorted into quintiles based on the level of forecast dispersion. Dispersion is defined as the ratio of the standard deviation of analysts' current fiscal year earnings forecasts to the absolute value of the mean forecast. Stocks with less than two analyst forecasts and stocks with a share price less than five dollars are excluded from the sample. I/B/E/S detail unadjusted file is used to derive the standard deviation and mean forecast. Stocks with mean forecast of zero are assigned to the highest dispersion group. Portfolios are updated monthly and returns are equal-weighted. The sample period is February 1984 through December 2011. Panel A shows the time-series average monthly raw returns. Panel B shows the Fama-French three-factor model alphas. Panel C shows the average dispersion. ***, ** , and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Raw Returns

Dispersion	Size					All stocks
	Small	2	3	4	Large	
Low	1.50	1.30	1.22	1.05	1.05	1.18
2	1.39	1.27	1.24	1.02	1.00	1.15
3	1.16	1.22	1.08	0.92	1.03	1.12
4	0.72	0.95	0.97	1.02	1.01	1.01
High	0.57	0.51	0.79	0.91	0.91	0.69
Low - High	0.94***	0.80***	0.43*	0.15	0.15	0.49**
NW t-stat	(3.96)	(3.42)	(1.76)	(0.62)	(0.58)	(2.02)

Panel B: FF (1993) three-factor alphas

Dispersion	Size					All stocks
	Small	2	3	4	Large	
Low	0.39**	0.30**	0.25**	0.13	0.22	0.24***
	(2.20)	(2.48)	(1.97)	(1.19)	(2.18)**	(2.75)
2	0.25	0.22	0.22**	0.06	0.11	0.15**
	(1.09)	(1.75)	(2.01)	(0.62)	(1.28)	(1.97)
3	0.02	0.13	0.04	-0.06	0.11	0.08
	(0.08)	(1.06)	(0.44)	(-0.71)	(1.21)	(1.11)
4	-0.51**	-0.23	-0.10	-0.04	0.02	-0.10
	(-2.00)	(-1.52)	(-0.98)	(-0.42)	(0.25)	(-0.92)
High	-0.72***	-0.73***	-0.40***	-0.21	-0.15	-0.52***
	(-2.65)	(-4.33)	(-3.04)	(-1.57)	(-1.08)	(-3.63)
Low - High	1.10***	1.03***	0.64***	0.34*	0.37*	0.76***
NW t-stat	(5.17)	(5.44)	(3.35)	(1.79)	(1.90)	(4.24)

Panel C: Average Dispersion

Dispersion	Size					All stocks
	Small	2	3	4	Large	
Low	0.011	0.010	0.010	0.011	0.011	0.010
2	0.042	0.030	0.026	0.024	0.021	0.027
3	0.090	0.060	0.049	0.043	0.036	0.051
4	0.195	0.126	0.100	0.085	0.066	0.108
High	0.943	0.655	0.521	0.447	0.309	0.588

Table 2.6 Forecast dispersion, direction of revisions, and future returns

This table reports the equally-weighted Fama-French three-factor alphas (t-statistics) of size and dispersion sorted stocks categorized by prior month's forecast revisions. Each month stocks are sorted into terciles based on the previous month's market capitalization, and further into terciles based on the previous month's forecast dispersion. The variables and the methodology are described in Table V. Panel A reports the results for stocks that experience an average upward revision away from the mean forecast in the previous month (diverging optimists). Panel B reports the results for stocks with an average downward revision away from the mean forecast (diverging pessimists). Panel C reports the results for stocks with an average downward revision towards the mean forecast (converging optimists). ***, ** , and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Portfolio of diverging optimists

Fama-French three-factor alphas (%) and t-statistics				
Dispersion	Size			All stocks
	Small	2	Large	
Low	0.68**	0.67***	0.19	0.39***
	(2.43)	(3.27)	(0.99)	(3.11)
2	0.60*	0.84***	0.44***	0.85***
	(1.82)	(3.66)	(2.56)	(6.01)
High	0.61*	0.10	0.17	0.21
	(1.71)	(0.38)	(0.75)	(1.15)
Low - High	0.06	0.58*	0.02	0.18
NW t-stat	(0.14)	(1.69)	(0.06)	(0.79)

Panel B. Portfolio of diverging pessimists

Fama-French three-factor alphas (%) and t-statistics				
Dispersion	Size			All stocks
	Small	2	Large	
Low	-0.29	-0.20	-0.14	-0.31**
	(-0.99)	(-1.01)	(-0.79)	(-2.43)
2	-1.40***	-0.30	-0.23	-0.31**
	(-4.18)	(-1.52)	(-1.48)	(-2.20)
High	-1.16***	-0.99**	-0.13	-1.03***
	(-3.01)	(-4.14)	(-0.57)	(-4.78)
Low - High	0.86**	0.79***	-0.01	0.72***
NW t-stat	(2.15)	(2.67)	(-0.04)	(3.20)

Panel C. Portfolio of converging optimists

Fama-French three-factor alphas (%) and t-statistics				
Dispersion	Size			All stocks
	Small	2	Large	
Low	-0.31*	-0.02	0.05	-0.05
	(-1.90)	(-0.14)	(0.41)	(-0.59)
2	-0.51***	-0.28**	0.00	-0.25**
	(-2.58)	(-2.15)	(-0.04)	(-2.39)
High	-1.08***	-0.61***	-0.19	-0.68***
	(-4.45)	(-4.11)	(-1.30)	(-4.84)
Low - High	0.77***	0.59***	0.23	0.63***
NW t-stat	(3.10)	(3.12)	(1.26)	(3.95)

Table 2.7 Fama-MacBeth (1973) regressions of monthly stock returns

The table reports the average slope coefficients (t-statistics) from monthly regressions of stock returns on firm characteristics and forecast revision proxies. The sample period is from January 1984 to December 2011. The dependent variable is the monthly percentage return of individual stocks. Beta, firm size, and the book-to-market ratio are estimated as in Fama and French (1992). *Lag Ret* is the compounded gross return between months t-7 and t-2. *Dispersion* is the natural logarithm of one plus the ratio of the standard deviation of analysts' current fiscal year earnings forecasts to the absolute value of the mean forecast in the prior month. Four dummy variables are interacted separately with *Dispersion*. *D(Opt_Div)* is a dummy variable that equals one if optimistic analysts as a group increased their forecasts in the previous month, and zero otherwise. *D(Opt_Con)* is a dummy variable that equals one if optimistic analysts as a group lowered their forecasts in the previous month, and zero otherwise. *D(Pes_Div)* is a dummy variable that equals one if pessimistic analysts as a group lowered their estimates in the previous month, and zero otherwise. *D(Con_Down)* is a dummy variable that equals one if the mean forecast decreased in the previous month, and zero otherwise. An analyst is defined as optimistic (pessimistic) if her forecast was above (below) the mean forecast prior to a revision in the previous month. The last column reports the average adjusted R-squares of the cross-sectional regressions. ***, ** , and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

						Interactions with Dispersion				
	Beta	Ln (B/M)	Ln (Size)	Lag Ret	Dispersion	D(Opt_Div)	D(Opt_Con)	D(Pes_Div)	D(Con_Down)	R2(%)
(1)	0.04	0.10	-0.04	0.78***	-0.71***					
	(0.13)	(1.10)	(-1.14)	(2.72)	(-4.34)					5.19
(2)	0.04	0.10	-0.04	0.77***	-0.74***	1.28**				
	(0.12)	(1.09)	(-1.15)	(2.68)	(-4.54)	(2.47)				5.24
(3)	0.04	0.10	-0.04	0.78***	-0.66***		-0.37**			
	(0.13)	(1.09)	(-1.13)	(2.71)	(-3.95)		(-2.07)			5.24
(4)	0.03	0.10	-0.04	0.78***	-0.66***			-0.81***		
	(0.11)	(1.08)	(-1.19)	(2.72)	(-3.91)			(-2.62)		5.24
(5)	0.04	0.10	-0.04	0.74**	-0.19				-1.00***	
	(0.12)	(1.09)	(-1.05)	(2.59)	(-0.93)				(-5.05)	5.28

Figure 2.1 Absolute cumulative abnormal return around forecast revisions

This figure plots the absolute value of the average percentage cumulative abnormal return during the three-days surrounding analysts' earnings forecast revisions, categorized by the direction of the revisions and the forecast dispersion. Abnormal returns are market-adjusted daily returns. Dispersion is calculated as the standard deviation of the earnings forecasts for the firm divided by the absolute value of the mean forecast using all eligible forecasts on the day prior to a forecast revision excluding the forecast being revised. The sample period is January 1984 to December 2011. The dashed line depicts average abnormal returns around upward forecast revisions and the solid line depicts average abnormal returns around downward forecast revisions.

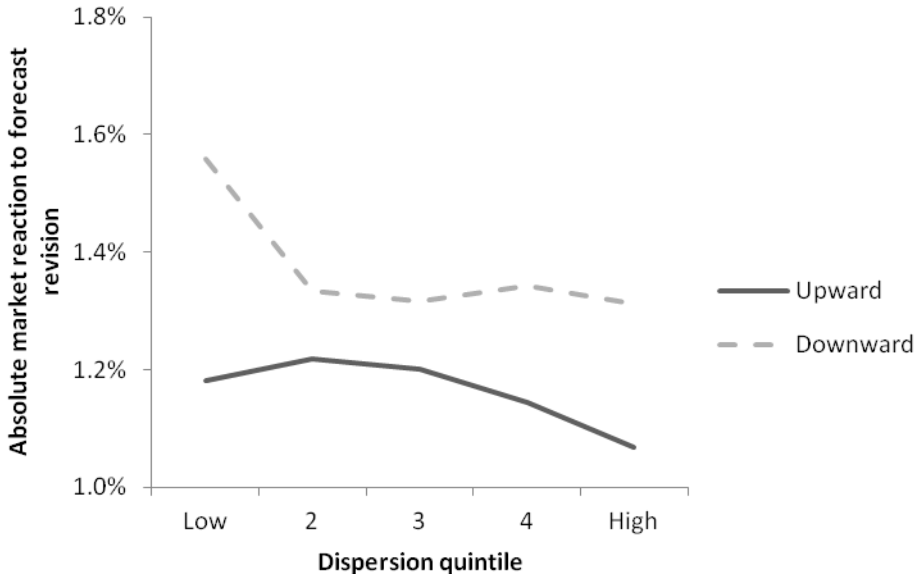

Figure 2.2 Abnormal returns of high dispersion stocks categorized by forecast revision

This figure plots the equally-weighted average Fama-French three-factor alphas of stocks in the highest dispersion quintile during the month of a forecast revision (t = 0) and the following six months. Stocks are categorized with respect to the direction of the revision and the relative optimism of the revising analysts. The dashed line depicts the returns to stocks with an average upward revision away from the mean forecast for the stock (diverging optimists). The solid black line depicts the returns to stocks with an average downward revision away from the mean forecast for the stock (diverging pessimists). The solid gray line depicts the returns to stocks with an average downward revision towards the mean forecast for the stock (converging optimists).

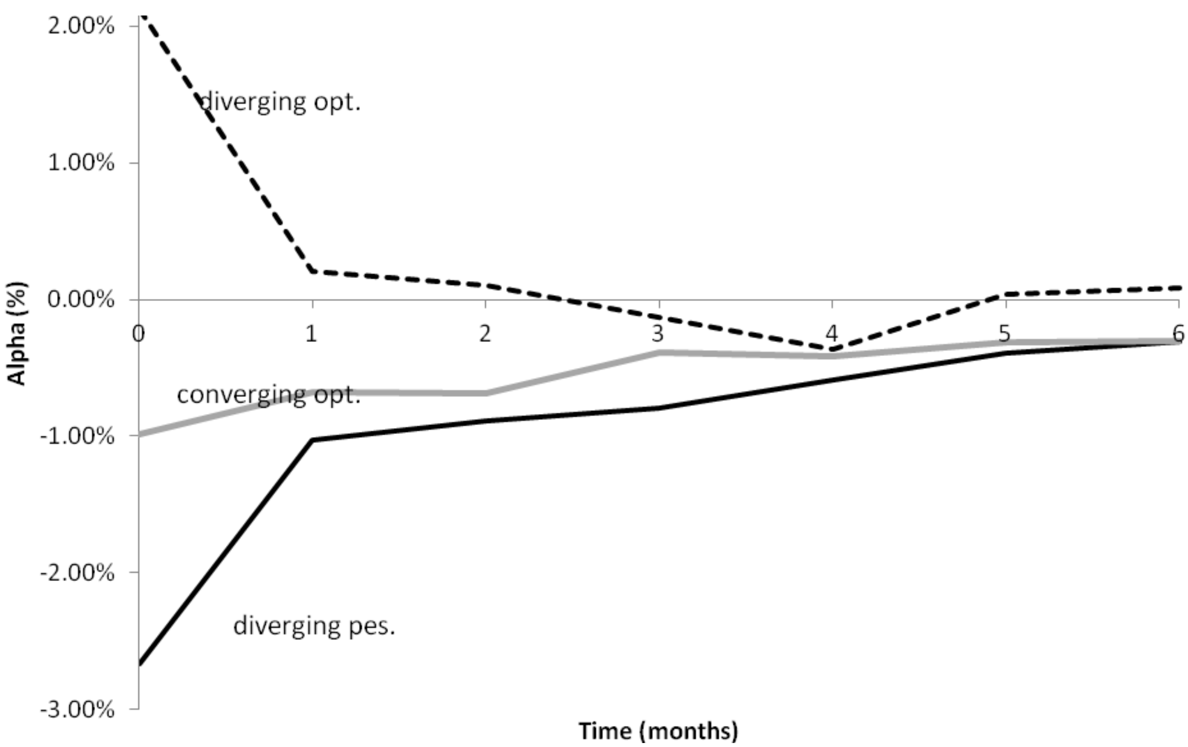

Figure 2.3 Forecast dispersion and the change in the consensus earnings forecast

This chart depicts the average change in the mean earnings forecast of stocks during the five months surrounding portfolio assignment based on firm size and the magnitude of forecast dispersion. All stocks are sorted into three size portfolios based on the market capitalization at the end of month t-1. Stocks in each size portfolio are then sorted into three dispersion portfolios based on the dispersion in analysts' earnings forecasts for the current fiscal year-end at the end of month t. The dashed black line depicts the average forecast revision of stocks with high dispersion and small market capitalization. The solid black line depicts the average forecast revision of stocks with low dispersion and small market capitalization. The dashed grey line depicts the average forecast revision of stocks with low dispersion and large market capitalization. The solid grey line depicts the average forecast revision of stocks with high dispersion and large market capitalization.

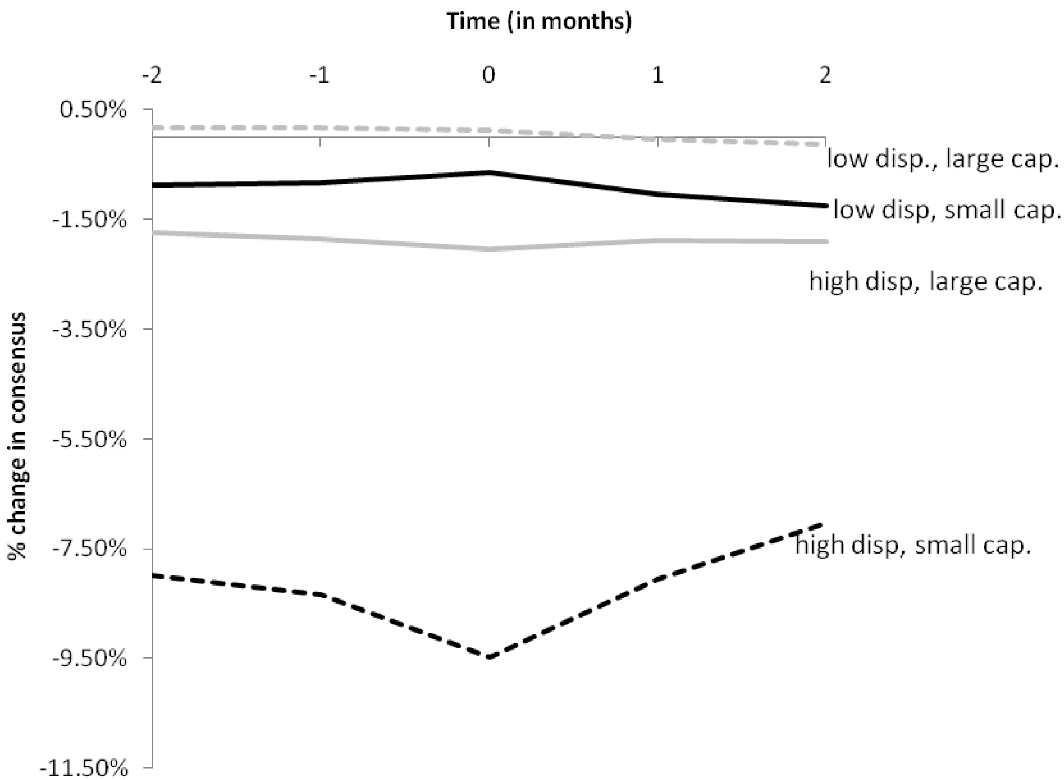

Figure 2.4 Time-series profitability of the dispersion strategy

We report the value over time of $1 invested in the dispersion strategy at the beginning of January 1984, separately for the full sample and the smallest 20% of stocks. The y-axis is in logarithmic scale for presentation purposes. Each month stocks are sorted into quintiles based on the level of forecast dispersion in the previous month. Dispersion is defined as the ratio of the standard deviation of analysts' current fiscal year earnings forecasts to the absolute value of the mean forecast. Stocks with less than two analyst forecasts and stocks with a share price less than five dollars are excluded from the sample. Stocks with mean forecast of zero are assigned to the highest dispersion group. Portfolios are updated monthly and equally weighted raw returns are recorded. The dispersion strategy takes a long position in the portfolio of stocks with the lowest dispersion and a short position in the portfolio with the highest dispersion. The dashed line represents the full sample of stocks. The solid black line represents the sample of small stocks.