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Heterogeneous Beliefs and Momentum Profits

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Abstract

Recent theoretical models derive return continuation in a setting where investors have heterogeneous beliefs or receive heterogeneous information. This paper tests the link between heterogeneity of beliefs and return continuation in the cross-section of U.S. stock returns. Heterogeneity of beliefs about a firm's fundamentals is measured by the dispersion in analyst forecasts of earnings. The results show that momentum profits are significantly larger for portfolios characterized by higher heterogeneity of beliefs. Predictive cross-sectional regressions show that heterogeneity of beliefs has a positive effect on return continuation after controlling for a stock's visibility, the speed of information diffusion, uncertainty about fundamentals, information precision, and volatility. The results in this paper are robust to the potential presence of short-sale constraints and are not explained by arbitrage risk.

I. Introduction

Since the momentum effect was first identified by Jegadeesh and Titman (1993), numerous papers have documented the profitability and robustness of momentum strategies both in domestic and international markets. Rational and behavioral theories have been developed to justify the existence of positive autocorrelation in returns.[1]

A recent and growing theoretical literature derives return continuation from settings in which investors are characterized by heterogeneity of beliefs or heterogeneity in information signals. Among the rational theories, Allen, Morris, and Shin (2006) develop a model in which higher-order beliefs lead to price drift. Banerjee, Kaniel, and Kremer (2009) show theoretically that differences of opinion, together with uncertainty about other agents' opinions, generate price drift in a dynamic setting. Makarov and Rytchkov (2009) present a rational model

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[1]For example, see Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999), and Johnson (2002).

of heterogeneously informed agents, which can generate momentum. Among the behavioral models, the framework of gradual information diffusion in Hong and Stein (1999) implies that investor heterogeneity is positively related to momentum. Hong and Stein (2007) characterize an economy where investors receive different information signals and erroneously believe that their signals are sufficient to forecast the asset liquidation value. The authors show that higher heterogeneity among investors implies stronger momentum.

This paper provides an empirical link between heterogeneity of beliefs and momentum. Using the dispersion of analysts forecasts of earnings to measure differences in investors' beliefs, I test the relation between disagreement and return continuation in a portfolio setting and in a regression framework.

I first perform a portfolio analysis and find that momentum profits increase with dispersion of beliefs. Monthly momentum profits for a portfolio of high-dispersion stocks are 55 basis points (bps) larger than profits for low-dispersion stocks (for the standard six-month ranking and holding periods). The difference is both statistically significant and economically important, and it represents over 50% of the momentum effect in the entire sample.

Previous studies show that return continuation is related to a stock's visibility and to the speed of information diffusion. For example, returns of stocks followed by more analysts lead returns of stocks with lower analyst coverage (Brennan, Jegadeesh, and Swaminathan (1993)); momentum profits are larger for stocks with smaller market capitalization and lower analyst coverage (Hong, Lim, and Stein (2000)); and stocks whose price incorporates information with a delay tend to be small, volatile, less visible, and neglected by many market participants (Hou and Moskowitz (2005)). I control for these effects in order to isolate the impact of differences in beliefs on momentum profits. By analyzing portfolios based on size, analyst coverage, book-to-market (BM), total volatility, idiosyncratic volatility, and exposure to the media, I find that momentum returns are larger for stocks that are characterized by higher disagreement. The differential in momentum profits is stronger among small stocks (reaching 69 bps per month), stocks with medium analyst coverage (89 bps), and stocks with high BM (79 bps).

I also analyze the role of turnover in conjunction with analyst forecast dispersion. Lee and Swaminathan (2000) show that momentum is stronger for stocks with higher trading volume. To the extent that both volume and forecast dispersion measure differences of opinion, momentum profits are likely to be related to both variables—under the hypothesis that differences in beliefs exacerbate return continuation. I find that turnover and forecast dispersion are both significantly related to momentum profits, suggesting that these variables may be capturing different aspects of heterogeneity in beliefs.

Finally, in the portfolio analysis, I investigate the role played by short-sale constraints in explaining the link between disagreement and momentum. I conclude that the potential presence of short-sale constraints does not explain the findings in this paper: After deleting from the sample all stocks that are likely to face short-sale constraints or high borrowing costs (see D'Avolio (2002)), I still find a significant differential in momentum between high- and low-dispersion stocks.

I then test the relation between heterogeneity of beliefs and return continuation in a multivariate regression setting. I estimate predictive cross-sectional regressions and find that differences in beliefs contribute to increasing the positive autocorrelation in six-month cumulative stock returns. First, I control for variables measuring a stock's visibility and the speed of information diffusion, as in the portfolio analysis. Furthermore, I control for the precision of information and for investors' prior uncertainty. In a Bayesian framework, investors update their beliefs by combining their prior beliefs with new information. The outcome of this updating process depends on two factors: the strength of investors' prior beliefs (prior uncertainty) and the precision of new information (information uncertainty). It is important to take both factors into account while testing for the effect of heterogeneity of beliefs on the speed of incorporation of information into prices.

The analysis of investor disagreement, prior uncertainty, and information uncertainty in relation to momentum is still a largely unexplored issue. Zhang (2006) views forecast dispersion as a measure of information uncertainty and tests the conjecture that it may lead to slower incorporation of information into prices. He finds that the one-month return differential between stocks of high and low forecast dispersion is larger for winners than for losers, concluding that information uncertainty exacerbates momentum. A number of omitted factors could, however, affect return continuation: measures of the speed of information diffusion, as shown in previous empirical studies; investors' prior uncertainty, as specified in Bayesian theory; and differences in beliefs, as derived explicitly in the rational and behavioral models described and tested in this paper. The analyst forecasts collected by the Institutional Brokers' Estimate System (IBES) do not provide a direct measure of the individual uncertainty associated with each point forecast. Therefore, I construct the following variables to control for investor uncertainty and the precision of information: i) the standard deviation of forecasts issued by an analyst for a given stock over a period of time, to capture the strength of the analyst's beliefs; ii) the average forecast error of all analysts covering a given stock, to measure uncertainty around the true value of a stock's fundamentals; iii) changes in forecast dispersion during the ranking period, to capture convergence or divergence of beliefs, and thus the precision of the information released about a firm; and iv) the persistence of a company's earnings process, to measure the reliability of new information signals.

The regression results show that heterogeneity of beliefs increases the association between past and future returns after controlling for measures of investor uncertainty, information precision, and the speed of information diffusion. In general, the regression estimates show that the degree of autocorrelation in six-month returns almost doubles when moving from the low to the high decile of forecast dispersion.

I also examine the impact of systematic and idiosyncratic risk on return continuation by controlling for a stock's beta and for idiosyncratic volatility. In line with the theory of Shleifer and Vishny (1997), risk-averse arbitrageurs may find an impediment to exploiting the momentum anomaly among stocks characterized by high idiosyncratic risk. These stocks would therefore exhibit higher momentum profits. Ali, Hwang, and Trombley (2003) find that the BM anomaly is stronger among stocks with higher idiosyncratic volatility, and thus they argue that the BM effect is in part attributable to limits to arbitrage. Hou and Moskowitz (2005) find that the price of stocks with higher residual volatility exhibits more severe delays in the incorporation of information. To control for arbitrage risk, I include measures of total and idiosyncratic volatility in the regression specification. While the results show that idiosyncratic risk has a strong incremental effect on return continuation, the effect of disagreement remains significant.

Finally, I control for media exposure using a subsample of stocks with data on news coverage. Media exposure is a direct measure of a stock's visibility among the investing public. I find that the effect of forecast dispersion on momentum is not subsumed by the effect of media exposure.

The rest of the paper develops as follows. Section II briefly discusses the main testable predictions of the theories of heterogeneous beliefs and return continuation. Section III describes the data. Section IV presents the results of the portfolio analysis, and Section V examines the impact of disagreement on return continuation in a regression setting. Section VI concludes the paper.

II. The Empirical Link between Heterogeneous Beliefs and Return Continuation

The goal of this paper is to empirically test the relation between differences in beliefs and return continuation that has been developed in several recent theoretical models. These models differ in their assumptions and in their implications, but they all assume heterogeneity in investors' beliefs or information and derive positive autocorrelation in stock returns. The empirical tests conducted in this paper are a cross-sectional investigation of the link between belief heterogeneity and return continuation. In the portfolio analysis, I test the hypothesis that momentum profits are higher for stocks characterized by higher heterogeneity of beliefs. Analogously, in the regression analysis I test the hypothesis that return autocorrelation in six-month cumulative individual stock returns is higher for stocks with a larger degree of heterogeneity of beliefs.

Makarov and Rytchkov (2009) show that heterogeneous information can lead to momentum. The models of Allen et al. (2006) and Banerjee et al. (2009) focus on the role of higher-order beliefs in generating price drift. In Allen et al. (2006), investors are engaged in a beauty contest and need to elicit other investors' beliefs about fundamentals. Prices differ from the consensus expectation of fundamental asset values and react sluggishly to changes in fundamentals, thus exhibiting drift. Banerjee et al. (2009) show that, in a dynamic setting, differences of opinion generate price drift if they are not common knowledge. In both these models, differences in beliefs are a necessary condition for price drift.

Among the behavioral models of momentum, Hong and Stein (1999) present a gradual information diffusion framework that links investor heterogeneity to return autocorrelation. Their model implies that higher heterogeneity in the economy (represented by a larger number of population groups receiving different information signals) leads to higher positive autocorrelation in returns.[2] Hong

[2]Hong and Stein (1999) assume that z different groups of investors who do not learn from prices (newswatchers) observe only one different piece of information each. Since the various pieces of news

and Stein (2007) derive the prediction that the strength of momentum profits is directly related to the degree of heterogeneity of beliefs. Investors receive different information signals and erroneously believe that their signals are sufficient to forecast the asset liquidation value. The authors show that momentum is strongest when there is maximal heterogeneity among investors.

Empirical work on differences of opinion is limited by the difficulty of measuring subjective beliefs and expectations. A number of studies rely on surveys or on proprietary data. As in several recent papers, I use the dispersion of analyst forecasts of earnings to measure differences of opinion about fundamentals.[3] The models of heterogeneous private information assume that investors do not see other investors' information signals and thus need to forecast the forecasts of others. Similarly, Banerjee et al. (2009) show that, in models of higher-order beliefs, a necessary condition for price drift is the lack of common knowledge, or the assumption that investors are uncertain about other investors' opinions. The use of forecast dispersion as a measure of investor heterogeneity seems at odds with these assumptions, since analyst forecasts are public information. However, analyst forecasts can be viewed as summary statistics resulting from underlying beliefs and models used by analysts to process information. Such beliefs and models are heterogeneous and unobservable but correlated with the summary forecasts issued by analysts. Forecast dispersion, therefore, can be used as an observable measure of the underlying unobservable heterogeneity.

In testing the link between heterogeneity of beliefs and momentum, it is important to distinguish the role of disagreement from investors' prior uncertainty and from information uncertainty. In a Bayesian setting, investors update their beliefs upon receiving new information. This updating process depends on the strength of investors' prior beliefs and on the precision of the information they receive. Both strong prior beliefs (corresponding to low ex ante uncertainty) and noisy information can hinder the process of incorporation of new information into prices. Lewellen and Shanken (2002), for example, derive return predictability in a setting where a rational Bayesian agent is uncertain about the parameters of the dividend process and updates her beliefs gradually. With uninformative priors, returns exhibit reversals, but informative priors can lead to return continuation. Zhang (2006) views forecast dispersion as information uncertainty and, analyzing portfolios sorted by past returns and forecast dispersion, finds that the one-month return differential between high- and low-dispersion stocks is positive for past winners and negative for past losers. It is difficult in this setting to disentangle the effect of forecast dispersion from the effect of other factors potentially correlated with past returns and dispersion, and previously associated with delays in the transmission of information (e.g., size, turnover, analyst coverage, and

rotate among investors gradually, only after z periods do all investors share the same information, implying gradual information diffusion into prices and positive return autocorrelation.

[3] Diether, Malloy, and Scherbina (2002) use the dispersion of analyst forecasts to measure differences of opinion. See also Verardo (2004). Ajinkya and Gift (1985) is an earlier study that uses dispersion of analyst forecasts as a measure of heterogeneity. Another possible measure of belief heterogeneity is breadth of ownership, introduced in Chen, Hong, and Stein (2002) and defined as the number of institutional investors with long positions in a particular stock. However, this measure is only available at a quarterly frequency.

volatility).[4] Furthermore, besides information uncertainty, it is important to consider the role of disagreement and the role of investors' prior uncertainty.

In this paper, I analyze the effect of belief heterogeneity on momentum while controlling for i) prior uncertainty, ii) information uncertainty, and iii) other stock characteristics that capture cross-sectional variation in the speed of information diffusion: size, BM, analyst coverage, turnover, volatility, and media coverage. I control for investors' prior uncertainty by constructing the following variables: the standard deviation of the forecasts issued by an analyst for a given stock over a period of time; the average forecast error of all analysts covering a given stock; and the persistence of a company's earnings process. Higher prior uncertainty should lead to faster updating of beliefs in the presence of new information. I also control for the precision of information by using changes in forecast dispersion during the ranking period. Lower information precision should lead to a lower speed of information diffusion.

I then check that the effect of heterogeneity of beliefs on momentum is not subsumed by systematic risk, and I control for idiosyncratic volatility to estimate the impact of arbitrage risk on momentum returns. Finally, I examine the role of trading volume. Lee and Swaminathan (2000) find a positive association between volume and momentum. To the extent that volume is a measure of disagreement, this finding could be consistent with the theories of heterogeneity of beliefs and price drift. In Hong and Stein (2007), the magnitude of the momentum effect increases not only with investor heterogeneity, but also with trading volume. Thus, I include share turnover in my analysis of disagreement and return continuation.

III. Data

The sample used in this study consists of monthly data for firms listed on NYSE, AMEX, and NASDAQ for the period 1984–2000.[5] Information on returns, prices, and firm characteristics is obtained from the Center for Research in Security Prices (CRSP), while BM comes from Compustat. Information on analyst forecasts is obtained from the IBES Detail History file.[6]

Each month I use the dispersion of analyst forecasts of earnings for the current fiscal year-end to represent investors' heterogeneity of beliefs. Dispersion (DISP) is the coefficient of variation of analyst forecasts of earnings for the end of the current fiscal year, defined as the standard deviation of forecasts scaled by

[4]Zhang (2006) introduces a size sort in the portfolio analysis when stocks are conditionally sorted both on past returns and on past forecast revisions, to identify extremely good and extremely bad news. The return differential across dispersion is significant only for small stocks in the bad news group.

[5]I follow the standard convention and limit my analysis to common stocks of firms incorporated in the U.S. American Depositary Receipts (ADRs), Shares of Beneficial Interest (SBIs), certificates, units, Real Estate Investment Trusts (REITs), closed-end funds, and companies incorporated outside the U.S. are excluded from the sample.

[6]Since the summary measures provided by the IBES Historical Summary File often contain stale forecasts, I construct summary measures of analyst forecasts using the Detail File. At the end of each month I consider all outstanding forecasts of earnings per share for the current fiscal year-end. For each analyst, I take only the most recently issued forecast and discard any forecast issued before the previous fiscal year-end. If an analyst does not revise her forecast, I assume that she is implicitly confirming it.

the absolute value of the mean. I discard observations with a zero mean forecast of earnings (about 0.30% in my sample)[7] and include observations with a negative mean forecast. I require that firms have at least two forecasts at each point in time. For robustness, I measure forecast dispersion using the interquartile range of forecasts scaled by the absolute value of the mean (INTERQ). For this measure I require the presence of at least three analyst forecasts outstanding.

Table 1 presents descriptive statistics of the universe of stocks considered in this study. The numbers reported are annual averages of monthly cross-sectional summary statistics. As shown in the table, the number of firms covered by IBES has increased over time. The sample is skewed toward large firms, as the average firm belongs to the fifth–sixth NYSE market capitalization decile. Analyst coverage does not show any particular trend over time and varies between seven and 10 analysts, on average. Forecast dispersion varies from 20% to 44% and exhibits considerable right-skewness, revealed by the much lower medians. Turnover is the ratio between a stock's trading volume and its shares outstanding, in excess of the average turnover of the exchange where the stock is traded. Total monthly volatility is calculated from daily data as in French, Schwert, and Stambaugh (1987), $\sigma_t^2 = \sum_{d=1}^{D} r_{dt}^2 + 2\sum_{d=1}^{D-1} r_{dt}^2 r_{d+1,t}^2$, where D is the number of days in month t and r_{dt} are daily returns in month t. Idiosyncratic volatility is the standard deviation of the residuals from a regression of daily stock returns on the CRSP value-weighted market index during a period of six months. The requirement that firms be followed by at least two analysts reduces the total number of observations to about 45% of all CRSP-IBES firm-months, or 445,000 firm-months.

To control for the quantity of news available about a stock, I use the data set constructed by Chan (2003) for his study on media coverage and return drift. He randomly selects about one-quarter of all CRSP stocks during the period 1980–2000 and collects all dates in which a stock is mentioned in the headline of an article from a set of major news sources (the Dow Jones newswires, *The Wall Street Journal,* and other major U.S. newspapers). I select all stocks in my CRSP-IBES sample that are also covered in Chan (2003). The sample initially comprises 2,500 stocks; requiring the presence of forecast dispersion data reduces the sample to a set of over 2,100 stocks, for a total of 104,000 firm-month observations.

IV. Portfolio Analysis

In this section, I present results from portfolio strategies based on past returns and disagreement, where disagreement is measured by the dispersion of analyst forecasts. I find a positive association between momentum and forecast dispersion and test that the results still hold after controlling for variables that capture the speed of information diffusion and for variables that measure total and idiosyncratic volatility. I also check that the results are not driven by covariation

[7]The coefficient of variation of forecasts may be artificially inflated for firms with a mean forecast (consensus) very close to 0. Although the highest decile of dispersion is in fact associated with the smallest average consensus, the correlation between DISP and the absolute value of the consensus is −0.05. For robustness, I perform the main tests in the subsequent empirical analysis excluding firms with absolute mean forecast below the first, fifth, and 10th percentile of the absolute mean distribution. The results do not change.

TABLE 1

Descriptive Statistics

Table 1 presents descriptive statistics of the main variables in the sample. The statistics are cross-sectional means (or medians where indicated), averaged every year. The sample contains NYSE, AMEX, and NASDAQ firms with at least two analyst forecasts of fiscal year earnings in a given month. Data on analyst forecasts are from the Detail IBES File. The sample period is from January 1984 to December 2000. DISP is the average ratio between the standard deviation of analyst forecasts of earnings and the absolute value of the mean of the forecasts (coefficient of variation). Median DISP is the median coefficient of variation of forecasts. INTERQ is the ratio between the interquartile range of forecasts and the absolute value of the mean. Consensus is the mean forecast of earnings per share in each month. NYSE_CAP is the mean capitalization decile based on NYSE break-points. AN_COV is the average number of analysts issuing a forecast in a given month. BM is the average book-to-market. TURN is the average monthly ratio between volume and shares outstanding, in excess of the mean turnover of the exchange where the stock is traded. RET is the average monthly return. TOT_VOL is the average monthly volatility calculated from daily returns as in French, Schwert, and Stambaugh (1987). IDIO_VOL is the average standard deviation of the residual from a regression of daily stock returns on the value-weighted CRSP index during a six-month period.

Year	No. of Firms	DISP	Median DISP	INTERQ	Consensus	NYSE_CAP	AN_COV	BM	TURN	RET	TOT_VOL	IDIO_VOL
1984	1,272	0.3278	0.0760	0.4392	1.6206	5.63	9.86	0.76	0.33	–0.0042	0.0117	0.0196
1985	1,342	0.3953	0.0830	0.4997	1.3351	5.56	9.57	0.72	0.33	0.0224	0.0105	0.0193
1986	1,416	0.4131	0.1071	0.5248	1.1256	5.53	9.45	0.64	0.24	0.0070	0.0131	0.0216
1987	1,497	0.4360	0.0973	0.5498	1.0567	5.52	9.24	0.61	0.55	0.0012	0.0239	0.0259
1988	1,454	0.3058	0.0732	0.4016	1.0833	5.51	9.06	0.71	0.52	0.0162	0.0125	0.0217
1989	1,526	0.3159	0.0645	0.4032	1.3623	5.37	8.75	0.64	0.59	0.0144	0.0112	0.0205
1990	1,582	0.3617	0.0712	0.4690	1.1652	5.33	8.39	0.88	0.67	–0.0145	0.0217	0.0271
1991	1,544	0.3384	0.0713	0.4847	0.8881	5.64	8.36	0.75	0.87	0.0342	0.0198	0.0269
1992	1,657	0.2889	0.0555	0.4001	0.8917	5.68	7.88	0.59	0.79	0.0159	0.0176	0.0262
1993	1,857	0.2204	0.0519	0.2846	0.7784	5.57	7.98	0.50	0.69	0.0126	0.0159	0.0254
1994	2,011	0.2177	0.0463	0.2998	0.5525	5.50	7.67	0.49	0.92	–0.0009	0.0156	0.0251
1995	2,143	0.2027	0.0432	0.2686	0.7726	5.55	7.47	0.48	1.00	0.0238	0.0156	0.0246
1996	2,444	0.2671	0.0444	0.3533	1.0061	5.34	7.12	0.45	0.85	0.0148	0.0197	0.0267
1997	2,606	0.2312	0.0383	0.3154	0.9534	5.16	6.96	0.41	1.18	0.0192	0.0212	0.0273
1998	2,709	0.2938	0.0386	0.3842	0.9574	5.14	7.12	0.47	1.11	0.0039	0.0335	0.0324
1999	2,549	0.2779	0.0396	0.3402	1.5247	5.48	7.66	0.55	1.15	0.0203	0.0343	0.0342
2000	2,550	0.2638	0.0470	0.3298	1.2417	5.83	8.09	0.60	1.55	–0.0030	0.0564	0.0425

with risk factors. I then examine the impact of disagreement while controlling for media exposure as a proxy for a stock's visibility. Furthermore, I analyze the interaction between forecast dispersion and turnover in affecting momentum profits. Last, I check the robustness of the results to the potential impact of short-sale constraints.

A. Momentum and Forecast Dispersion

I form momentum portfolios focusing on the six-month ranking period and the six-month holding period strategy that is usually examined in momentum studies. Specifically, at the end of each month I form portfolios of stocks ranked on the basis of their returns over the previous six months, and I compute the average return to such portfolios over the subsequent six months. Returns to the zero-investment strategy that buys winners and sells losers represent momentum profits. I follow the calendar methodology used by Jegadeesh and Titman (1993) to obtain correct inferences and address the problem of serial correlation in the presence of overlapping return periods.

Panel A of Table 2 confirms the presence of momentum profits in my sample. I report average monthly returns for the top portfolio of winners, the intermediate portfolio, and the bottom portfolio of losers. Ranking stocks into three groups based on past returns yields a strongly significant average momentum profit of 0.93% per month. The magnitude of the returns is similar to previous findings in the momentum literature despite the severe restrictions adopted in the sample selection process, which reduce the sample and bias it toward large firms.[8]

TABLE 2

Momentum and Forecast Dispersion

Table 2 presents average monthly returns for portfolio strategies based on past returns and analyst forecast dispersion. The sample period is from January 1984 to December 2000. Each month, stocks are sorted into three portfolios based on their previous six-month returns; portfolios are held for six months. R1 is the portfolio of past losers, and R3 is the portfolio of past winners. Momentum strategies consist of buying the winner portfolio and selling the loser portfolio (R3 – R1). In Panel A, stocks are sorted into three portfolios based on past returns. The table shows descriptive statistics of the momentum portfolios. In Panel B, stocks are sorted into three portfolios based on past returns and independently sorted into three groups based on analyst forecast dispersion measured at portfolio formation. DISP1 (DISP3) represents the lowest (highest) dispersion portfolio. Average returns are in percent per month, and *t*-statistics are in parentheses.

Panel A. Momentum Portfolios

Momentum Portfolio	RET	DISP	INTERQ	NYSE CAP	AN_COV	BM	TURN	TOT_VOL	IDIO_VOL
R1	0.62 (1.51)	0.4793	0.6389	4.69	8.06	0.80	1.00	0.0268	0.0310
R2	1.15 (3.49)	0.2167	0.2754	6.08	8.89	0.60	–0.41	0.0131	0.0213
R3	1.54 (3.62)	0.2320	0.2904	5.80	8.18	0.46	2.12	0.0213	0.0260
R3 – R1	0.93 (3.91)								

Panel B. Returns to Momentum-Dispersion Portfolios

Momentum Portfolio	DISP1	DISP2	DISP3	DISP3 − DISP1
R1	0.91 (2.53)	0.71 (1.79)	0.40 (0.88)	
R2	1.29 (4.11)	1.12 (3.39)	0.97 (2.52)	
R3	1.49 (4.01)	1.59 (3.69)	1.53 (3.07)	
R3 – R1	0.57 (3.01)	0.88 (3.62)	1.13 (4.32)	0.55 (3.59)

For the winner, the intermediate, and the loser portfolios, Table 2 presents summary statistics of stock characteristics measured at portfolio formation. There are apparent nonlinearities in the characteristics of these portfolios, since they exhibit more extreme values for winners and losers. As can be seen from the table, market capitalization varies with momentum in a nonmonotonic fashion. It first increases with ranking period returns and then decreases, describing an inverted U-shaped pattern. The data also indicate that beliefs are more heterogeneous for losers than for winners. Average turnover is also U-shaped across momentum portfolios. Both total and idiosyncratic volatility are larger for losers and winners than for the intermediate portfolio.

To test the hypothesis that heterogeneity of beliefs is related to momentum, I form portfolios by sorting stocks on the basis of past returns and dispersion of

[8]If I rank stocks into deciles, the strategy of buying winners and selling losers yields an average return of 1.86% per month. The rest of this study focuses on three momentum portfolios. The goal is not to document the existence of large momentum profits but rather to assess variations in momentum profits across subsamples of stocks.

analyst forecasts. Specifically, I rank all stocks into three groups based on their previous six-month returns and then rank stocks independently into three groups based on their forecast dispersion measured at the end of the month preceding portfolio formation. The intersection yields nine portfolios, whose returns are shown in Panel B of Table 2. Momentum returns are significant and increase monotonically with forecast dispersion. The difference in momentum returns between the high- and the low-dispersion portfolios is 55 bps per month and strongly significant (the p-value is smaller than 0.001). The profit differential is economically important, given that it represents about 50% of the total momentum effect in the sample.[9]

To check for the robustness of the results to alternative measures of forecast dispersion, I repeat the portfolio analysis of Table 2 using the interquartile range of forecasts. The untabulated findings are very similar to the results obtained using the coefficient of variation: Momentum strategies for high-dispersion stocks yield returns that are 56 bps higher than the momentum returns of low-dispersion stocks. I conclude that the results are not specific to the measure of dispersion chosen and conduct the rest of the analysis using the coefficient of variation (DISP).

Winners and losers contribute roughly equally to the momentum profits shown in Table 2. In all dispersion categories, the return spread between the medium and the loser portfolios does not differ greatly from the return spread between the winner and the medium portfolios, relative to the total momentum profits. Past losers account for about 67% of total profits for low-dispersion stocks, 47% of profits for medium-dispersion stocks, and 50% of momentum profits for high-dispersion stocks.[10] These results differ from those of Hong et al. (2000), who find that momentum profits come mainly from past losers, and are consistent with Jegadeesh and Titman (2001), who show that winners and losers contribute equally to momentum profits. In an interesting feature of the results, losers are mostly responsible for the variation in momentum profits across dispersion portfolios. As can be seen from Table 2, the difference in momentum between high and low dispersion is justified by variations in returns among past losers. In Hong et al. (2000), the momentum differential between high- and low-analyst-coverage stocks is also mainly explained by differences in returns for loser portfolios.

To assess whether the covariance with possible risk factors can explain the positive difference in momentum between high- and low-dispersion portfolios, I estimate the Fama-French (1993) three-factor model for the monthly series of

[9]The statistical inference reported in this study refers to two-sided significance tests. However, the hypothesis tested is that momentum profits are larger in the presence of greater heterogeneity of beliefs, due to a slower process of information diffusion. The conjectures from the theoretical papers cited in this study point to unidirectional tests. In this sense, the two-sided p-values reported above can be taken as conservative. The same reasoning applies to all significance tests conducted throughout the paper.

[10]For example, for high-dispersion stocks, the difference between 40 bps and 97 bps (loser and medium past returns) is roughly the same as the difference between 97 bps and 153 bps (medium and winner portfolios).

momentum-dispersion returns, net of the risk-free rate.[11] Specifically, the dependent variables of the regressions are the excess returns for portfolios of past losers, past winners, and momentum in each of the low-, medium-, and high-forecast dispersion categories. Moreover, this time-series test is performed for the difference in momentum returns between high- and low-dispersion portfolios:

$$(R_W - R_L)_t^{\mathrm{HIGH}} - (R_W - R_L)_t^{\mathrm{LOW}} = a_p + b_p(R_{Mt} - r_{ft}) + s_p \mathrm{SMB}_t + h_p \mathrm{HML}_t + \varepsilon_{pt}.$$

The estimated coefficients are reported in Table 3. Interesting common features emerge from these findings. In general, momentum studies show that winners and losers have approximately the same beta, while losers typically have higher loadings on the SMB and HML factors. Analyzing the results across dispersion categories, the regression coefficients show that momentum portfolios with low disagreement tend to have lower loadings on the SMB factor and higher (less negative) loadings on the HML factor. The estimates of the intercept are all positive and significant. More importantly, the intercepts for the difference in momentum profits between high- and low-dispersion portfolios are very similar to the average estimates reported using total returns, and are sometimes higher. In conclusion, after adjusting for market risk, size, and BM characteristics, the momentum return differential between high- and low-dispersion stocks remains positive and significant.

TABLE 3

Time-Series Tests for Momentum-Dispersion Portfolios

Table 3 reports coefficient estimates from the Fama-French (1993) three-factor model for monthly excess returns of portfolios sorted on past returns and dispersion of forecasts. R1 is the portfolio of past losers, R3 is the portfolio of past winners. DISP1 is the low-dispersion portfolio, and DISP3 is the high-dispersion portfolio. The sample period is from January 1984 to December 2000. The parameters reported in the table are estimated from the following regression: $(R_{pt} - r_{ft}) = a_p + b_p(R_{mt} - r_{ft}) + s_p\mathrm{SMB}_t + h_p\mathrm{HML}_t + e_{pt}$. The intercept estimates are in percentage points, and t-statistics are adjusted for heteroskedasticity and shown in parentheses.

Dispersion	Momentum Portfolio	a	b	s	h	Adj. R^2
DISP1	R1	–0.45 (–2.48)	1.0858 (23.43)	0.3378 (5.77)	0.3457 (4.83)	0.7685
	R3	0.22 (1.94)	1.0906 (38.16)	0.4612 (12.78)	0.1111 (2.52)	0.9168
	R3 – R1	0.66 (3.59)	0.0048 (0.10)	0.1234 (2.06)	–0.2346 (–3.21)	0.1321
DISP2	R1	–0.64 (–3.47)	1.1414 (24.05)	0.4686 (7.82)	0.2507 (3.42)	0.7986
	R3	0.40 (4.16)	1.1274 (45.78)	0.7280 (23.41)	–0.0613 (–1.61)	0.9544
	R3 – R1	1.04 (4.59)	–0.0140 (–0.24)	0.2593 (3.53)	–0.3120 (–3.47)	0.2005
DISP3	R1	–0.93 (–4.37)	1.2063 (22.07)	0.8584 (12.43)	0.3136 (3.72)	0.8011
	R3	0.34 (2.63)	1.2055 (36.32)	0.9908 (23.64)	–0.0822 (–1.61)	0.9382
	R3 – R1	1.27 (5.11)	–0.0008 (–0.01)	0.1323 (1.64)	–0.3959 (–4.02)	0.1587
DISP3 – DISP1	R3 – R1	0.61 (3.86)	–0.0056 (–0.14)	0.0089 (0.18)	–0.1612 (–2.59)	0.0415

[11]The series of SMB, HML, and excess market returns are obtained from Ken French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/).

B. Momentum, Forecast Dispersion, and Stock Characteristics

In the analysis that follows, I compute momentum returns for portfolios of stocks that are sorted on past returns, forecast dispersion, and, alternatively, one of the following variables: market capitalization, analyst coverage, BM, total volatility, or idiosyncratic volatility. These variables have been related to return continuation in previous empirical studies. Furthermore, I estimate intercepts from time-series regressions of momentum returns on the Fama-French (1993) factors to verify that the profits from the momentum strategies are not driven by covariation with potential risk factors.

To control for size, I sort stocks independently into terciles of market capitalization, past returns, and forecast dispersion, forming 27 portfolios of about 160 to 320 stocks, on average. The first column in Table 4 presents average monthly returns for the zero-investment strategy that buys winners and sells losers for different portfolios of forecast dispersion and market capitalization. As with most anomalies, the momentum differential across dispersion is especially strong among smaller stocks, where the difference in momentum profits between high- and low-dispersion portfolios $(\text{DISP3} - \text{DISP1})$ is about 0.69% and is statistically significant. For stocks in the medium- and large-size groups, the difference is positive, although not significant at conventional levels. The economic importance of these differences in momentum across dispersion groups can be better understood if compared to the benchmark momentum returns originated by a strategy based only on size and past returns. In my sample, untabulated tests reveal that momentum returns are 1.29% for small stocks, 0.90% for medium capitalization stocks, and 0.48% for large stocks. Therefore, heterogeneity of beliefs explains about 53% of the momentum profits coming from small stocks (the ratio between 0.69% and 1.29%). Analogously, the difference in heterogeneity of beliefs accounts for 20% of momentum for the medium-sized portfolio and 68% of momentum for large firms.

The number of analysts following a stock has been used as a proxy for the speed of information diffusion. Brennan et al. (1993) find that returns on stocks with higher analyst coverage lead returns on stocks followed by fewer analysts. Hong et al. (2000) show that momentum is stronger for stocks that are followed by fewer analysts. Hou and Moskowitz (2005) find a negative association between analyst coverage and a measure of information delay. In summary, broader analyst coverage is associated with less drift in stock returns. In this study, I investigate the relation between disagreement and momentum after accounting for the quantity of information available about a stock. I ask whether, for a given level of analyst coverage, heterogeneity of beliefs slows down the process of incorporation of information into prices. Given the high correlation between size and analyst coverage in my sample (about 0.46), I follow Hong et al. (2000) and examine the effect of residual analyst coverage, defined as the residual obtained from regressing analyst coverage on size. Each month, I estimate the following cross-sectional regression:

$$\ln(1 + \text{AN\_COV}_{i,t}) \quad = \quad \alpha_t + \beta_t \ln(\text{SIZE}_{i,t}) + \varepsilon_{i,t},$$

TABLE 4

Momentum Returns to Dispersion-Characteristics Portfolios

Table 4 presents average monthly momentum returns from portfolio strategies based on past returns, dispersion of beliefs, and, alternatively, one of the following stock characteristics: size (CAP), residual analyst coverage (RESNA), book-to-market (BM), total volatility (TOT_VOL), or idiosyncratic volatility (IDIO_VOL). The sample period is from January 1984 to December 2000. Each month, stocks are sorted into three portfolios based on past returns and independently sorted into three groups based on analyst forecast dispersion measured at portfolio formation. DISP1 (DISP3) represents the lowest (highest) dispersion portfolio. Stocks are also independently sorted into three groups based on stock characteristics. The table shows average six-month holding period returns from buying the winner portfolio and selling the loser portfolio for each dispersion-characteristic portfolio. Returns are in percent per month. The *t*-statistics are in parentheses.

Dispersion	Size	Residual Coverage	Book-to-Market	Total Volatility	Idiosyncratic Volatility
	CAP1	RESNA1	BM1	TOT_VOL1	IDIO_VOL1
DISP1	0.87	0.57	1.04	0.15	0.16
	(4.23)	(2.69)	(4.87)	(1.00)	(0.99)
DISP3	1.56	1.06	1.69	0.48	0.46
	(6.39)	(3.80)	(5.37)	(2.80)	(2.51)
DISP3 – DISP1	0.69	0.49	0.65	0.33	0.30
	(3.75)	(2.62)	(2.70)	(2.30)	(2.04)
	CAP2	RESNA2	BM2	TOT_VOL2	IDIO_VOL2
DISP1	0.65	0.45	0.28	0.53	0.56
	(3.27)	(2.34)	(1.52)	(3.04)	(3.07)
DISP3	0.83	1.33	0.91	0.87	0.87
	(2.79)	(5.01)	(3.70)	(4.04)	(3.86)
DISP3 – DISP1	0.18	0.89	0.63	0.34	0.31
	(0.92)	(4.64)	(3.02)	(2.10)	(1.90)
	CAP3	RESNA3	BM3	TOT_VOL3	IDIO_VOL3
DISP1	0.24	0.74	0.18	1.24	1.15
	(1.13)	(3.40)	(0.93)	(4.90)	(4.62)
DISP3	0.58	1.17	0.97	1.48	1.46
	(1.73)	(4.13)	(4.43)	(5.01)	(5.01)
DISP3 – DISP1	0.33	0.43	0.79	0.24	0.30
	(1.50)	(1.81)	(3.86)	(1.27)	(1.60)

where $\text{AN\_COV}_{i,t}$ is the number of analysts following firm i in month t.[12] Given estimates of the parameters α_t and β_t, I then obtain estimates of $\varepsilon_{i,t}$, the residual number of analysts (denoted RESNA).

The second column in Table 4 shows returns to momentum portfolios sorted by residual analyst coverage and forecast dispersion. Momentum strategies remain more profitable for stocks with higher heterogeneity of beliefs. The return differentials between high- and low-dispersion portfolios are all large and significantly positive. The difference in momentum returns between the high- and low-dispersion groups is 0.49% for low residual coverage (significant at the 1% level), 0.89% for medium residual coverage (significant at the 1% level), and 0.43% for high residual coverage (significant at the 10% level).[13] In comparison, Hong

[12]With this specification for analyst coverage, the dependent variable increases at a decreasing rate with the number of analysts. Adding more independent variables in the regression model does not change the results, therefore I choose the more parsimonious specification. The model generates an adjusted R^2 of 0.62.

[13]If I consider the total number of analysts instead of residual analyst coverage, the difference in momentum profits between the high- and low-heterogeneity portfolios is larger for the medium-analyst-coverage portfolios (0.86%), it decreases but remains important for the low-coverage stocks (0.58%), and is still positive but not statistically significant at conventional levels for the high-coverage

et al. (2000) find a difference of about 0.42% in momentum returns between high- and low-residual analyst coverage groups and interpret this result as evidence that stocks with slower information diffusion exhibit more pronounced momentum. The prediction that slower information diffusion implies larger return continuation and thus larger momentum profits (as modeled in Hong and Stein (1999)) is not contradicted by the evidence in this paper. The findings in this study suggest that, holding constant the quantity of information available about a stock (measured by size and analyst coverage), disagreement slows down the incorporation of information into prices and exacerbates return continuation.

There is evidence of a significant association between momentum profits and BM. Asness (1997) shows that momentum strategies are significantly stronger among growth (low BM) stocks. Daniel et al. (1998) argue that growth stocks are likely to exhibit more momentum. I sort stocks into portfolios on the basis of past returns, forecast dispersion, and BM (which is measured at the end of the previous fiscal year so as to guarantee its availability to the investing public at portfolio formation). The difference between high- and low-dispersion momentum is still present after controlling for BM, as can be seen in the third column of Table 4. The momentum return differential is high and strongly significant for all BM portfolios and ranges from 0.63% to 0.79% per month.[14]

I next control for total and idiosyncratic volatility of returns. As Shleifer and Vishny (1997) note, high idiosyncratic risk could deter risk-averse arbitrageurs from exploiting market anomalies. To the extent that high forecast dispersion is subsumed by high idiosyncratic volatility, the result that momentum is larger for high-dispersion stocks could be driven by arbitrage risk. The correlation between forecast dispersion and idiosyncratic volatility is 12% in my sample. The last two columns of Table 4 show that the momentum differential between high- and low-dispersion stocks is positive in all volatility portfolios, and more strongly significant among stocks characterized by lower total and idiosyncratic volatility.

Finally, to control for exposure to risk factors, Table 5 presents Fama-French (1993) intercept estimates for momentum portfolios based on forecast dispersion and each of the stock characteristics previously examined. The intercepts from these time-series regressions confirm the positive and significant momentum differential between high- and low-dispersion stocks across the various stock characteristics.

C. News Headlines

In this section, I examine the interaction between media exposure and disagreement in explaining return continuation. Chan (2003) establishes an association between media exposure and momentum, documenting that stocks with news

stocks. However, controlling for the number of analysts leaves considerable variation in size across dispersion portfolios.

[14]I also compute the returns to momentum strategies excluding negative BM firms from the sample. The results on momentum profits remain substantially unaltered, with differences in momentum between high- and low-dispersion groups ranging from 0.65% to 0.78%.

TABLE 5

Time-Series Tests for Momentum-Dispersion-Characteristics Portfolios

Table 5 reports intercept estimates from the Fama-French (1993) three-factor model. The dependent variable is the monthly momentum profit obtained from portfolios sorted on past returns, analyst forecast dispersion, and, alternatively, one of the following characteristics: size (CAP), residual analyst coverage (RESNA), book-to-market (BM), total volatility (TOT_VOL), or idiosyncratic volatility (IDIO_VOL). DISP1 (DISP3) represents the lowest (highest) dispersion portfolio. The sample period is from January 1984 to December 2000. The parameters reported in the table are the estimated intercepts from the regression: $(R_{pt} - r_{ft}) = a_p + b_p(R_{mt} - r_{ft}) + s_p \mathrm{SMB}_t + h_p \mathrm{HML}_t + e_{pt}$. The intercept estimates are in percent per month, and t-statistics are adjusted for heteroskedasticity and shown in parentheses.

Dispersion	Size	Residual Coverage	Book-to-Market	Total Volatility	Idiosyncratic Volatility
	CAP1	RESNA1	BM1	TOT_VOL1	IDIO_VOL1
DISP1	0.94 (4.66)	0.72 (3.71)	1.15 (5.34)	0.12 (0.80)	0.14 (0.93)
DISP3	1.61 (6.71)	1.27 (5.17)	1.79 (5.78)	0.46 (2.64)	0.45 (2.41)
DISP3 – DISP1	0.67 (3.51)	0.55 (2.93)	0.64 (2.62)	0.35 (2.41)	0.31 (2.06)
	CAP2	RESNA2	BM2	TOT_VOL2	IDIO_ VOL2
DISP1	0.70 (3.73)	0.48 (2.48)	0.39 (2.10)	0.58 (3.53)	0.58 (3.51)
DISP3	1.10 (4.00)	1.44 (5.73)	0.92 (3.64)	0.90 (4.28)	0.87 (4.02)
DISP3 – DISP1	0.40 (2.07)	0.97 (5.11)	0.53 (2.46)	0.33 (1.98)	0.29 (1.73)
	CAP3	RESNA3	BM3	TOT_VOL3	IDIO_VOL3
DISP1	0.38 (1.87)	0.77 (3.46)	0.13 (0.66)	1.32 (5.86)	1.19 (5.44)
DISP3	0.85 (2.83)	1.23 (4.24)	0.87 (3.83)	1.56 (6.01)	1.53 (6.09)
DISP3 – DISP1	0.47 (2.19)	0.46 (1.85)	0.74 (3.51)	0.24 (1.25)	0.33 (1.70)

headlines exhibit return drift while stocks with no news show no evidence of momentum. The analysis in this paper adds a layer to these findings and focuses on the contribution of disagreement to return continuation after controlling for the quantity of news available about a stock.

I select all stocks in my CRSP-IBES sample that are also covered in Chan (2003). To construct his sample, Chan randomly selects about one-quarter of all CRSP stocks during the period 1980–2000 and collects all dates in which a stock is mentioned in the headline of an article from a set of major news sources (the Dow Jones newswires, *The Wall Street Journal,* and other major U.S. newspapers). I first check whether the momentum-dispersion differential is still present in this reduced sample. I find that high-dispersion stocks exhibit larger momentum than low-dispersion stocks, with a return differential of 0.71% (the standard error is 0.23%). I then form portfolios by ranking stocks on the basis of past returns, forecast dispersion, and an indicator variable for the presence of any news headlines in the month preceding portfolio formation. The results are based on independent sorts and are reported in Table 6. In each of the two news portfolios, the momentum differential between high- and low-dispersion stocks is large and statistically significant and of similar magnitude. Momentum differences between high- and low-dispersion stocks are 0.80% for no-news stocks and 0.72% for news stocks, and statistically significant.[15] However, within each dispersion portfolio the momentum differential between news and no-news stocks is very small and not significant (average returns range from −0.33% to 0.17%).[16] These results suggest that disagreement is important beyond a stock's visibility: Higher heterogeneity of beliefs contributes to increasing momentum after controlling for a stock's media exposure.

TABLE 6

Momentum, Forecast Dispersion, and News Headlines

Table 6 presents average monthly returns from portfolio strategies based on past returns, dispersion of beliefs, and an indicator function for the presence of news headlines in month *t*. Stocks belong to the intersection of the sample used in this paper and the sample constructed by Chan (2003), covering the period 1984–2000. Each month, stocks are sorted into news and no-news portfolios, and independently sorted into three groups based on their past returns. R1 is the portfolio of past losers, and R3 is the portfolio of past winners. Stocks are also independently sorted on the dispersion of analyst forecasts measured during the month that precedes portfolio formation. DISP1 (DISP3) represents the lowest (highest) dispersion portfolio. Momentum profits are average six-month holding period returns from buying the winner portfolio and selling the loser portfolio (R3 – R1). Returns are in percent per month, and *t*-statistics are in parentheses.

Dispersion	Momentum Portfolio	NO_NEWS	NEWS	NEWS – NO_NEWS
DISP1	R1	0.89 (2.23)	0.84 (2.24)	
	R3	1.38 (3.84)	1.49 (3.88)	
	R3 – R1	0.49 (2.07)	0.65 (2.83)	0.17 (0.72)
DISP2	R1	0.50 (1.20)	0.68 (1.64)	
	R3	1.79 (4.23)	1.63 (3.75)	
	R3 – R1	1.29 (4.15)	0.96 (3.70)	–0.33 (–1.33)
DISP3	R1	0.29 (0.59)	0.36 (0.76)	
	R3	1.58 (3.27)	1.73 (3.40)	
	R3 – R1	1.29 (4.18)	1.38 (4.62)	0.09 (0.27)
DISP3 – DISP1	R3 – R1	0.80 (2.07)	0.72 (2.91)	

D. Trading Volume

In this section, I investigate the relation between momentum, trading volume, and forecast dispersion. Lee and Swaminathan (2000) show that momentum is stronger for stocks with higher trading volume. Whether the volume-momentum profitability is driven by forecast dispersion or whether volume subsumes forecast dispersion in explaining momentum is an empirical question that depends on the

[15]Unreported tests show that conditioning first on news and then ranking independently on past returns and forecast dispersion yields similar profit differentials of 0.67% for no-news stocks (significant at the 8% level) and 0.73% for news stocks (significant at the 1% level). Measuring news over the entire six-month ranking period yields very similar results for all specifications.

[16]Momentum differentials between news and no-news stocks within a specific dispersion portfolio range from 0.09% to −0.08% when stocks are ranked conditionally on news, dispersion, and, finally, past returns.

underlying phenomenon that these two variables are capturing. To the extent that both volume and forecast dispersion measure differences of opinion, momentum profits are likely to be related to both variables—under the hypothesis that differences in beliefs imply return continuation. The model in Hong and Stein (2007) derives a role for volume as a measure of disagreement and as a cause of momentum.

I sort stocks into three portfolios based on the daily average excess turnover calculated over the month that precedes portfolio formation.[17] First, I consider three momentum portfolios and find a positive association between share turnover and momentum in my sample. The difference in momentum returns between high- and low-volume stocks is 0.65%, which is statistically significant and economically important. I then sort stocks independently on forecast dispersion. Table 7 shows that both turnover and forecast dispersion affect momentum profits. The difference in momentum across dispersion portfolios, holding turnover constant, is 0.61% and 0.52% for low and medium turnover, respectively, and it decreases to 0.27% for high-turnover stocks. Analogously, the difference in momentum across turnover, holding dispersion constant, is large and significant for low- and medium-dispersion stocks (0.78% and 0.75%, respectively), and it is smaller for high-dispersion stocks (0.43%). Both variables provide independent information about future return continuation patterns. Only for high turnover does dispersion not contribute to higher-momentum profits. On the other hand, turnover is only weakly associated with momentum when dispersion is relatively high.

E. Short-Sale Constraints

With the premise that short-sale constraints are pervasive and that they prevent pessimistic beliefs from being impounded into prices, Diether et al. (2002) test the hypothesis formulated in Miller (1977) that, in a heterogeneous agent economy, prices reflect overoptimism due to the presence of short-sale constraints. They find that portfolios of stocks with high forecast dispersion earn lower returns than stocks with low dispersion in the month after portfolio formation. The positive association between momentum profits and heterogeneity of beliefs could be consistent with this short-sale hypothesis. The fact that high-dispersion losers earn lower returns than low-dispersion losers during the holding period is consistent with the idea that heterogeneity of beliefs slows the process of information diffusion and exacerbates return continuation. This result is also consistent with the idea that high-dispersion losers are more subject to short-sale constraints and are overpriced, and thus undergo a correction phase in the future.

Are short-sale constraints more binding for stocks with poor past performance and high disagreement? D'Avolio (2002) finds that while small size and low institutional ownership increase the probability that a stock is special (i.e., it

[17] While Lee and Swaminathan (2000) use total turnover and exclude NASDAQ stocks from their sample (because of the double-counting of dealer trades in NASDAQ), I adopt a unifying measure of turnover for NYSE, AMEX, and NASDAQ stocks. I define daily excess turnover as a stock's daily turnover minus the average daily turnover of the exchange in which the stock is traded. The results do not change if I define excess turnover as the ratio of individual turnover to exchange turnover, or if I divide NASDAQ turnover by 2.

TABLE 7

Momentum, Forecast Dispersion, and Turnover

Table 7 presents average monthly returns from portfolio strategies based on past returns, dispersion of forecasts, and turnover for the period 1984–2000. Each month, stocks are sorted into three portfolios based on their previous six-month returns. R1 is the loser portfolio, and R3 is the winner portfolio. Stocks are independently sorted into three groups based on their excess turnover during the month that precedes portfolio formation. Excess turnover is defined with respect to the average monthly turnover of the exchange where the stock is traded. TURN1 (TURN3) is the portfolio with the lowest (highest) turnover. Stocks are also independently sorted on the dispersion of analyst forecasts measured during the month that precedes portfolio formation. DISP1 (DISP3) represents the lowest (highest) dispersion portfolio. Momentum profits are average six-month holding period returns from buying the winner portfolio and selling the loser portfolio (R3 – R1). Returns are in percent per month, and *t*-statistics are in parentheses.

Dispersion	Momentum Portfolio	TURN1	TURN2	TURN3	TURN3 – TURN1
DISP1	R1	1.09	1.02	0.43	
		(3.52)	(2.82)	(0.95)	
	R3	1.45	1.47	1.58	
		(4.69)	(4.16)	(3.30)	
	R3 – R1	0.36	0.45	1.14	0.78
		(2.18)	(2.40)	(4.45)	(3.72)
DISP2	R1	0.91	0.80	0.41	
		(2.71)	(2.14)	(0.83)	
	R3	1.48	1.51	1.73	
		(4.49)	(4.01)	(3.25)	
	R3 – R1	0.57	0.71	1.32	0.75
		(2.73)	(3.31)	(4.56)	(3.58)
DISP3	R1	0.48	0.48	0.21	
		(1.16)	(1.10)	(0.39)	
	R3	1.45	1.45	1.62	
		(3.62)	(3.42)	(2.77)	
	R3 – R1	0.98	0.97	1.41	0.43
		(4.48)	(3.95)	(4.54)	(1.85)
DISP3 – DISP1	R3 – R1	0.61	0.52	0.27	
		(3.59)	(2.95)	(1.23)	

has high lending fees), the fact that a stock is a past loser does not have a strong effect on the costs of borrowing it.[18] Geczy, Musto, and Reed (2002) replicate momentum strategies, taking into account the constraints from short-selling on a daily basis, and find that the expected return difference between constrained and unconstrained momentum strategies is too small to offset the returns to the unconstrained strategy. In relation to heterogeneity of beliefs, D'Avolio (2002) finds that dispersion of analyst forecasts does not play any role in explaining borrowing costs.[19]

I provide here some direct evidence that the positive link between momentum profits and disagreement is not determined by a strategy based on shorting stocks that are in fact difficult or impossible to sell short. D'Avolio (2002) finds that most of the stocks in the CRSP files are easy to short, and that stocks with no short interest are typically small and illiquid. The stocks that are potentially unshortable (because they are difficult to locate among institutional lenders) constitute only 0.6% of the total CRSP market value. The author documents that the

[18]Logit estimates of the probability that a stock is special show that being prescribed as a short in a momentum strategy (involving a standard six-month ranking period) has a positive and significant effect on borrowing costs only four months out of 18 months.

[19]Logit estimates of the likelihood that a stock is special show that dispersion of analyst forecasts has a negative average coefficient but is insignificant in all 18 months that constitute the sample period.

bottom one-third of the stocks in the lowest NYSE size decile and about one-third of stocks priced below $5 appear unshortable, and argues that these stocks should be excluded from trading strategies that might prescribe short positions (like momentum). In my sample, the requirement that stocks have at least two analyst forecasts outstanding at each point in time already excludes most of the stocks with a price below $5 or a market capitalization in the lowest NYSE decile. I repeat the portfolio analysis excluding all stocks priced below $5 and all stocks belonging to the bottom 10% of the NYSE capitalization distribution (about 4% of the observations in the sample). The momentum differential between high- and low-dispersion stocks is now 0.46% and remains strongly significant, with a p-value of 0.2%. This result shows that the association between momentum and disagreement is mostly driven by factors unrelated to short-sales restrictions.

V. Regression Analysis

In this section, I investigate the association between heterogeneity of beliefs and return continuation in a multivariate regression setting. I use the Fama-MacBeth (1973) methodology to estimate predictive cross-sectional regressions of the six-month cumulative return of stock i on the same stock's past return, measured in the previous six months, and other stock characteristics that are potentially related to future returns.[20] The goal of this analysis is to investigate the effect of disagreement on the association between past and future returns and to disentangle such effect from the impact of other variables.

A. Regression Model and Results

I estimate predictive cross-sectional regressions using the following specification:

$$\begin{aligned} R_{i,t+1:t+6} \quad = \quad & a_t + b_{1t}\text{PAST\_RET}_{i,t} + b_{2t}(\text{DISP}_{i,t} * \text{PAST\_RET}_{i,t}) \\ & + b_{3t}(\text{TURN}_{i,t} * \text{PAST\_RET}_{i,t}) + b_{4t}(\text{UNCERTAINTY}_{i,t} * \text{PAST\_RET}_{i,t}) \\ & + b_{5t}(\text{PRECISION}_{i,t} * \text{PAST\_RET}_{i,t}) + b_{6t}(\text{VOLATILITY}_{i,t} * \text{PAST\_RET}_{i,t}) \\ & + b_{7t}(\text{BETA}_{i,t} * \text{PAST\_RET}_{i,t}) + b_{8t}\text{DISP}_{i,t} + b_{9t}\text{TURN}_{i,t} \\ & + b_{10t}\text{UNCERTAINTY}_{i,t} + b_{11t}\text{PRECISION}_{i,t} + b_{12t}\text{VOLATILITY}_{i,t} \\ & + b_{13t}\text{BETA}_{i,t} + b_{14t}\text{CAP}_{i,t} + b_{15t}\text{RESNA}_{i,t} + b_{16t}\text{BM}_{i,t} + \varepsilon_{i,t}, \end{aligned}$$

where the variables are defined as follows: $R_{i,t+1:t+6}$ is the cumulative return for stock i measured during the months $t+1$ to $t+6$; $\text{PAST\_RET}_{i,t}$ is the past return of stock i measured during the months $t-5$ to t. The coefficient b_1 is thus a measure of the autocorrelation in six-month returns. $\text{DISP}_{i,t}$ is the dispersion of analyst forecasts for stock i measured in month t. $\text{TURN}_{i,t}$ is the ratio between a stock's trading volume and its shares outstanding in month t, in excess of the average

[20]For robustness, I obtain coefficient estimates from a pooled regression with clustered standard errors. The estimation results (not shown for brevity) are consistent with those obtained from the Fama-MacBeth (1973) procedure, and the statistical significance is stronger.

turnover of the exchange where the stock is traded. UNCERTAINTY$_{i,t}$ is a measure of ex ante uncertainty about a company's fundamentals. Several variables are used to capture investor uncertainty:

i) The standard deviation of an analyst's forecasts of earnings for stock i over a fiscal year, STD_FOR$_{i,t}$, averaged across analysts. This variable measures the uncertainty of an analyst's beliefs about the prospects of a firm, after controlling for the quantity of information released about a company.

ii) The mean squared forecast error of analyst forecasts for company i over a fiscal year, MSFE$_{i,t}$, averaged across analysts. Larger forecast errors indicate higher uncertainty.

iii) The persistence of a firm's earnings process. Shocks to earnings that are perceived to be permanent are likely to have larger price effects than temporary shocks and a different impact on the speed of incorporation of information into prices. I estimate the following ARIMA(0,1,1) process for annual earnings:

$$X_{i,t} - X_{i,t-1} \quad = \quad \mu_i + \varepsilon_{i,t} - \theta_i \varepsilon_{i,t-1},$$

and use the variable $(1 - \theta_i)$ as a measure of earnings persistence.[21]

PRECISION$_{i,t}$ captures the precision of the information released on company i during the past six months and is measured by the change in forecast dispersion, ΔDISP$_{i,t}$. An increase in forecast dispersion suggests low information precision and thus a slower updating process, leading to more return continuation. VOLATILITY$_{i,t}$ measures either total or idiosyncratic return volatility for stock i during the past six months: i) Total monthly volatility is calculated as $\sigma_t^2 = \sum_{d=1}^{D} r_{dt}^2 + 2\sum_{d=1}^{D-1} r_{dt}^2 r_{d+1,t}^2$, where D is the number of days in month t and r_{dt} are daily returns in month t; and ii) Idiosyncratic volatility is the standard deviation of the residuals from a regression of stock i's daily returns on the value-weighted market index during the previous six months. Alternative periods for the estimation of market model regressions do not alter the results. BETA$_{i,t}$ is the slope estimate from a market model regression of daily returns of stock i during the previous six months.

The model specification includes interaction terms to allow for the slope coefficient of past returns to vary with these measures of heterogeneity of beliefs, uncertainty, information precision, and volatility. These interaction terms capture the extent to which the autocorrelation in returns varies cross-sectionally with heterogeneity of beliefs and all the control variables. A positive estimate of b_2 implies that return continuation is stronger for firms with larger disagreement. Similarly, b_3 captures the contribution of turnover to return continuation, b_4 captures the impact of individual uncertainty, b_5 measures the effect of the precision of news,

[21]With this specification, revisions in earnings expectations are an increasing function of $(1 - \theta)$. Alternatively, I estimate the following seasonal random walk model using quarterly data:

$$X_{i,t} - X_{i,t-4} \quad = \quad \mu_i + \varphi_i (X_{i,t-1} - X_{i,t-5}) + u_{i,t},$$

where φ_i is the persistence parameter. The results are similar to those reported for annual data. See Collins and Kothari (1989) for a review of the literature examining the persistence of earnings processes.

b_6 reflects the incremental effect of volatility, and, finally, b_7 measures the contribution of systematic risk to momentum. All the control variables interacted with past returns are also included independently in the regression to capture their main effect on future returns. Other control variables included in the regression are a firm's market capitalization, BM ratio, and residual analyst coverage (number of analysts orthogonalized with respect to size). All explanatory variables are measured in decile ranks. The coefficients are estimated in monthly cross-sectional regressions and are then averaged over time, following the Fama-MacBeth (1973) procedure. Inference is drawn based on the standard deviation of the series of estimates. The standard errors are then corrected using the Newey-West (1987) methodology to account for the autocorrelation in the error term induced by overlapping cumulative returns.

Panels A and B of Table 8 display the regression results. Consistent with the portfolio results, forecast dispersion has a positive and significant effect on return continuation. Consider, for example, the specification in the second column of Panel A in Table 8. If a stock moves from the loser portfolio (bottom decile of past returns) to the winner portfolio (top decile of past returns), the marginal increase in future six-month returns is about 2.9% for low-dispersion stocks. This effect almost doubles to 5.3% if a stock has high forecast dispersion.[22]

Forecast dispersion predicts future returns with a negative coefficient, consistent with Diether et al. (2002). As seen in the portfolio analysis, both forecast dispersion and turnover contribute to increasing the autocorrelation in returns. The negative effect of turnover on future returns is consistent with an illiquidity premium argument. For example, Brennan, Chordia, and Subrahmanyam (1998) find that stocks with high trading volume tend to earn low future returns.

Past changes in forecast dispersion have a negative effect on future returns but a positive effect on return continuation. To the extent that this variable captures the precision of information released during the ranking period, the estimates suggest that noisier information (an increase in dispersion) is associated with slower incorporation of information into prices.

The variables that measure investor uncertainty are associated with less momentum. Both $\text{STD\_FOR}_{i,t}$ and $\text{MSFE}_{i,t}$ have negative slope coefficients when interacted with past returns. This finding is consistent with the intuition from Bayesian theory that more ex ante uncertainty (more diffuse priors) implies faster updating of beliefs upon receiving new information, and thus less return continuation.

The variables capturing the persistence of the earnings process are associated with more momentum. This finding suggests that investors underreact more to permanent shocks to earnings. This result needs to be interpreted with caution, however, since the inclusion of earnings persistence in the specification reduces the sample size and selects only firms with a sufficiently long earnings history.

[22]In this example, turnover is held constant at the value of 1 (low turnover decile). The marginal effect of past returns on cumulative future returns is given by

$$\frac{\partial R_{i,t+1:t+6}}{\partial \text{PAST\_RET}_{i,t}} = \widehat{b_1} + \widehat{b_2} * \text{DISP}_{i,t} + \widehat{b_3} * \text{TURN}_{i,t}.$$

A stock's beta does not have any incremental effect on return continuation. This finding is not surprising in light of the numerous empirical studies on momentum that fail to explain this anomaly by systematic risk. Idiosyncratic risk, however, contributes substantially to return continuation. Both total volatility and idiosyncratic volatility have large positive coefficients when interacted with past returns. The finding that return continuation is stronger in the presence of higher arbitrage risk suggests the potential presence of impediments to the elimination of the momentum anomaly by risk-averse arbitrageurs, consistent with Shleifer and

TABLE 8

Cross-Sectional Regressions

Table 8 presents estimates of Fama-MacBeth (1973) predictive cross-sectional regressions for individual stock returns from January 1984 to December 2000. The dependent variable is the six-month cumulative stock return ($R_{t+1:t+6}$). PAST_RET is the six-month cumulative past return ($R_{t-5:t}$); DISP is analyst forecast dispersion, measured at the end of month t; TURN is excess turnover, measured at the end of month t; ΔDISP is the change in forecast dispersion during the previous six months; STD_FOR is the average standard deviation of forecasts for firm i during the previous fiscal year; MSFE is the mean squared forecast error for firm i during the previous fiscal year; PERSISTENCE is a measure of persistence of the firm's earnings process, $(1-\theta)$, where θ is the MA coefficient of an ARIMA(0,1,1) process for earnings; TOT_VOL is average monthly volatility of stock i, estimated from daily data as in French, Schwert, and Stambaugh (1987); BETA is the slope estimate of a market model regression estimated from daily data during the past six months; IDIO_VOL is the standard deviation of the residual from a market model regression estimated from daily data during the past six months; CAP is market capitalization, measured at the end of month t; RESNA is residual analyst coverage (number of analysts orthogonalized by size), measured at the end of month t; BM is the book-to-market ratio, measured at the end of month t. All explanatory variables are expressed in decile ranks; t-statistics are adjusted for autocorrelation following Newey-West (1987) and shown in parentheses.

Panel A. Basic Specifications

Independent Variables					
PAST_RET	0.0055 (3.73)	0.0022 (1.40)	0.0031 (1.80)	0.0061 (2.70)	–0.0035 (–2.07)
PAST_RET * DISP	0.0004 (2.83)	0.0003 (2.20)	0.0007 (3.74)	0.0006 (2.96)	0.0004 (2.21)
DISP	–0.0044 (–2.05)	–0.0039 (–1.90)	–0.0046 (–1.95)	–0.0041 (–1.77)	–0.0018 (–0.83)
PAST_RET * TURN		0.0007 (2.72)	0.0007 (2.87)	0.0007 (2.87)	0.0007 (2.77)
TURN		–0.0039 (–3.33)	–0.0038 (–3.31)	–0.0037 (–3.20)	–0.0019 (–1.47)
ΔDISP			–0.0012 (–1.64)	–0.0016 (–2.30)	–0.002 (–2.88)
PAST_RET * ΔDISP			0.0001 (1.21)	0.0002 (1.87)	0.0002 (1.77)
MSFE			0.0016 (3.75)	0.0013 (3.27)	0.0009 (2.53)
PAST_RET * MSFE			–0.0007 (–4.17)	–0.0013 (–5.42)	–0.0014 (–6.14)
STD_FOR				0.0039 (2.24)	–0.0028 (–1.90)
PAST_RET * STD_FOR				0.0001 (0.36)	0.0008 (2.72)
PERSISTENCE					–0.0021 (–2.13)
PAST_RET * PERSISTENCE					0.0007 (4.68)
CAP	0.0011 (0.68)	0.0011 (0.63)	0.0015 (0.89)	0.0016 (0.98)	–0.0019 (–1.21)
RESNA	0.0013 (2.09)	0.0013 (2.19)	0.0012 (1.91)	0.0010 (1.71)	0.0010 (1.68)
BM	0.0036 (1.36)	0.0036 (1.50)	0.0045 (1.95)	0.0046 (2.10)	0.0030 (1.54)

(continued on next page)

TABLE 8 (continued)

Cross-Sectional Regressions

Panel B. Specification Including Beta and Volatility Measures

Independent Variables					
PAST_RET	–0.0002 (–0.16)	–0.0034 (–2.21)	0.0023 (1.10)	–0.0007 (–0.42)	–0.0038 (–2.22)
PAST_RET ∗ DISP	0.0003 (1.98)	0.0004 (2.34)	0.0007 (3.74)	0.0003 (1.98)	0.0003 (2.03)
DISP	–0.0022 (–1.34)	–0.0016 (–1.01)	–0.0046 (–1.96)	–0.0019 (–1.26)	–0.0012 (–0.78)
PAST_RET ∗ TURN	0.0003 (1.65)	0.0005 (2.71)	0.0006 (2.99)	0.0002 (1.89)	0.0005 (3.10)
TURN	–0.0009 (–0.89)	–0.001 (–0.90)	–0.0032 (–2.96)	–0.0011 (–1.18)	–0.001 (–0.90)
ΔDISP	–0.0014 (–2.29)	–0.0022 (–3.38)	–0.0013 (–1.68)	–0.0009 (–1.38)	–0.0022 (–3.39)
PAST_RET ∗ ΔDISP	0.0001 (1.60)	0.0002 (2.02)	0.0001 (1.30)	0.0001 (0.75)	0.0002 (2.01)
MSFE	0.0016 (4.46)	0.0008 (2.94)	0.0016 (3.60)	0.0013 (3.73)	0.0007 (2.51)
PAST_RET ∗ MSFE	–0.0007 (–5.49)	–0.001 (–9.09)	–0.0007 (–4.27)	–0.0008 (–6.23)	–0.001 (–9.11)
PERSISTENCE		–0.0023 (–2.59)			–0.0025 (–2.85)
PAST_RET ∗ PERSISTENCE		0.0008 (5.61)			0.0008 (5.74)
TOT_VOL	–0.0088 (–5.63)	–0.0033 (–2.85)			
PAST_RET ∗ TOT_VOL	0.0012 (7.10)	0.0007 (3.82)			
BETA			–0.0005 (–0.67)	0.0018 (1.62)	0.0014 (2.17)
PAST_RET ∗ BETA			0.0003 (1.55)	0.0001 (0.75)	0.0001 (0.36)
IDIO_VOL				–0.0111 (–8.86)	–0.0046 (–4.22)
PAST_RET ∗ IDIO_VOL				0.0014 (7.48)	0.0007 (4.07)
CAP	0.0009 (0.80)	–0.0018 (–1.70)	0.0015 (0.85)	–0.0001 (–0.07)	–0.0025 (–2.24)
RESNA	0.0012 (2.42)	0.0011 (2.17)	0.0010 (1.67)	0.0007 (1.49)	0.0010 (2.13)
BM	0.0038 (2.58)	0.0027 (1.98)	0.0047 (2.19)	0.0038 (2.80)	0.0029 (2.10)

Vishny (1997).[23] Nevertheless, the incremental effect of forecast dispersion does not disappear, suggesting the presence of a robust link between heterogeneity of beliefs and return continuation.

B. Media Coverage

I perform the same regression analysis on a subsample of stocks with data on media coverage. The sample comprises all firms that are also included in the study by Chan (2003) on news headlines and momentum. The regression

[23]The importance of arbitrage risk has been tested for the BM anomaly by Ali et al. (2003), who find that the BM effect is larger for stocks with higher idiosyncratic volatility.

TABLE 9

Cross-Sectional Regressions: With News Headlines

Table 9 presents estimates of Fama-MacBeth (1973) predictive cross-sectional regressions for individual stock returns. The sample includes all stocks belonging to the intersection between the sample used in this paper and the sample constructed in Chan (2003), covering the period 1984–2000. The dependent variable is the six-month cumulative stock return ($R_{t+1:t+6}$). NEWS is an indicator function that equals 1 if the stock has any news headlines in month t. NEWSDAYS is the number of days in which stock i has any news headlines in month t. All other variables are defined in Table 8; t-statistics are adjusted for autocorrelation following Newey-West (1987) and shown in parentheses.

Independent Variables					
PAST_RET	0.0069 (2.70)	0.0066 (2.63)	0.0036 (1.97)	0.0069 (2.51)	0.0036 (1.76)
PAST_RET ∗ DISP	0.0008 (2.43)	0.0008 (2.39)	0.0004 (1.96)	0.0008 (2.37)	0.0004 (1.78)
DISP	–0.0027 (–1.04)	–0.0023 (–0.89)	0.0000 (0.03)	–0.0021 (–0.78)	0.0003 (0.19)
PAST_RET ∗ TURN	0.0004 (0.99)	0.0004 (0.95)	–0.0001 (–0.23)	0.0003 (0.76)	0.0000 (0.10)
TURN	–0.0012 (–0.54)	–0.0009 (–0.43)	0.0018 (1.22)	–0.0004 (–0.20)	0.0014 (1.02)
ΔDISP	–0.0026 (–2.35)	–0.0023 (–2.13)	–0.0026 (–2.62)	–0.0024 (–2.15)	–0.0026 (–2.51)
PAST_RET ∗ ΔDISP	0.0003 (1.36)	0.0002 (1.15)	0.0003 (1.47)	0.0002 (1.21)	0.0003 (1.44)
MSFE	0.0069 (4.04)	0.0068 (4.03)	0.0069 (4.65)	0.0067 (4.02)	0.0067 (4.64)
PAST_RET ∗ MSFE	–0.001 (–4.16)	–0.001 (–4.19)	–0.001 (–5.16)	–0.001 (–4.00)	–0.001 (–4.98)
TOT_VOL			–0.0076 (–3.29)		
PAST_RET ∗ TOT_VOL			0.0011 (4.26)		
BETA				0.0004 (0.30)	0.0012 (1.13)
PAST_RET ∗ BETA				0.0001 (0.34)	0.000 (0.24)
IDIO_VOL					–0.008 (–3.81)
PAST_RET ∗ IDIO_VOL					0.0011 (4.41)
NEWS	–0.0021 (–0.25)				
PAST_RET ∗ NEWS	–0.001 (–0.76)				
NEWSDAYS		–0.0021 (–1.37)	–0.0023 (–1.97)	–0.0021 (–1.35)	–0.0028 (–2.30)
PAST_RET ∗ NEWSDAYS		0.0000 (0.07)	0.0001 (0.33)	0.0000 (0.23)	0.0001 (0.61)
CAP	0.0015 (0.73)	0.0023 (1.09)	0.0019 (1.32)	0.0025 (1.22)	0.0015 (1.00)
RESNA	0.0022 (2.30)	0.0022 (2.37)	0.0022 (2.87)	0.0021 (2.25)	0.0021 (2.65)
BM	0.0042 (1.92)	0.0043 (1.96)	0.0039 (2.68)	0.0046 (2.10)	0.0041 (2.68)

specification includes an indicator variable for the presence of any news headlines on stock i in month t, $\text{NEWS}_{i,t}$. Alternatively, media exposure is represented by $\text{NEWSDAYS}_{i,t} = \sum_t \text{NEWS}_{i,t}$, defined as the total number of days in month t on which at least one news headline about stock i appears in a major news source.

The regression estimates are presented in Table 9 and show that the quantity of news about a stock does not affect momentum: The interaction term between news and past returns is not significant and has a negative sign. The quantity of news does not seem to affect future returns either, since the coefficient estimate on media exposure is negative but not significant. Forecast dispersion still plays an important role in the continuation of returns. The coefficient estimate on the interaction term between dispersion and past returns is positive and significant. The effect of turnover on return continuation is also positive, but not statistically significant at conventional levels. All results are robust to measuring both $\text{NEWS}_{i,t}$ and $\text{NEWSDAYS}_{i,t}$ in the past six months.

C. Winners and Losers

To investigate whether the effect of disagreement on momentum varies with a stock's past performance, I interact the term $\text{DISP}_{i,t} * \text{PAST\_RET}_{i,t}$ with indicator variables for loser stocks (lowest tercile of past six-month returns) and winner stocks (highest tercile of past six-month returns).

Table 10 presents the estimates from the new specification. The slope coefficients show some evidence of asymmetry in relation to a stock's past performance. Consistent with the portfolio analysis, the effect of disagreement on momentum is slightly larger and more significant for loser stocks when fewer control variables are included in the regression specification. In the presence of volatility effects, however, the effect of disagreement on return continuation is stronger and more significant for winners, while it is weaker for past losers. This finding still holds after the inclusion of the persistence of the earnings process and its interaction with past returns.

VI. Conclusions

Recent theoretical papers derive return continuation by introducing heterogeneity of beliefs in rational or behavioral models of asset pricing. While measures of the speed of information diffusion have been empirically related to momentum profits, the link between disagreement and return continuation has not been previously tested.

Extant empirical research establishes that characteristics like a stock's visibility and the speed of information diffusion are positively associated with momentum in the cross-section of stock returns. Hong et al. (2000) show that stocks with lower analyst coverage exhibit more momentum. Hou and Moskowitz (2005) find that prices of stocks that are small, less visible, more volatile, and neglected by market participants incorporate information with a delay.

In this paper, I test the relation between differences in beliefs and return continuation in a portfolio setting and in a regression framework. Using the dispersion of analyst forecasts as a measure of heterogeneity in beliefs, I find that momentum profits are significantly larger for portfolios characterized by higher heterogeneity. This result holds for portfolios of stocks sorted by market capitalization, analyst coverage, BM, total volatility, and idiosyncratic volatility.

Cross-sectional predictive regressions confirm the positive association between disagreement and return continuation after controlling for a stock's visibility, the quantity and precision of information available about a company,

TABLE 10

Cross-Sectional Regressions: Winners and Losers

Table 10 presents estimates of Fama-MacBeth (1973) predictive cross-sectional regressions for individual stock returns. The dependent variable is the six-month cumulative stock return ($R_{t+1:t+6}$). W and L are indicator variables for the top 30% and the bottom 30% of the cross-sectional distribution of past returns, respectively. All other variables are defined in Table 8; t-statistics are adjusted for autocorrelation following Newey-West (1987) and shown in parentheses.

Independent Variables						
PAST_RET	0.0024	0.0034	–0.0004	0.0025	–0.001	–0.0042
	(1.47)	(1.91)	(–0.27)	(1.22)	(–0.55)	(–2.52)
PAST_RET ∗ DISP	0.0002	0.0006	0.0001	0.0006	0.0000	0.0000
	(1.13)	(2.48)	(0.38)	(2.67)	(0.10)	(0.18)
W ∗ PAST_RET ∗ DISP	0.0002	0.0001	0.0002	0.0001	0.0003	0.0003
	(1.69)	(1.27)	(3.37)	(1.28)	(4.45)	(4.40)
L ∗ PAST_RET ∗ DISP	0.0003	0.0003	0.0001	0.0004	0.0001	–0.0002
	(2.29)	(2.30)	(0.67)	(2.39)	(0.52)	(–1.47)
DISP	–0.0041	–0.0049	–0.0018	–0.0050	–0.0012	0.0001
	(–1.80)	(–1.87)	(–0.98)	(–1.94)	(–0.74)	(0.04)
PAST_RET ∗ TURN	0.0006	0.0007	0.0003	0.0005	0.0002	0.0005
	(2.60)	(2.75)	(1.48)	(2.83)	(1.74)	(3.04)
TURN	–0.0038	–0.0037	–0.0009	–0.0032	–0.0012	–0.0011
	(–3.26)	(–3.21)	(–0.85)	(–2.86)	(–1.29)	(–0.98)
ΔDISP		–0.0012	–0.0015	–0.0013	–0.0010	–0.0022
		(–1.62)	(–2.29)	(–1.66)	(–1.50)	(–3.48)
PAST_RET ∗ ΔDISP		0.0001	0.0001	0.0001	0.0001	0.0002
		(1.26)	(1.67)	(1.34)	(0.92)	(2.16)
MSFE		0.0016	0.0016	0.0015	0.0013	0.0007
		(3.73)	(4.44)	(3.57)	(3.70)	(2.47)
PAST_RET ∗ MSFE		–0.0007	–0.0007	–0.0007	–0.0008	–0.0010
		(–4.18)	(–5.52)	(–4.27)	(–6.23)	(–9.06)
PERSISTENCE						–0.0025
						(–2.84)
PAST_RET ∗ PERSISTENCE						0.0008
						(5.74)
TOT_VOL			–0.0091			
			(–5.97)			
PAST_RET ∗ TOT_VOL			0.0013			
			(7.15)			
BETA				–0.0004	0.0019	0.0015
				(–0.64)	(1.69)	(2.34)
PAST_RET ∗ BETA				0.0002	0.0001	0.0000
				(1.51)	(0.64)	(0.18)
IDIO_VOL					–0.0114	–0.0052
					(–9.16)	(–4.88)
PAST_RET ∗ IDIO_VOL					0.0014	0.0008
					(7.57)	(4.42)
CAP	0.0012	0.0016	0.0010	0.0016	0.0000	–0.0024
	(0.72)	(0.98)	(0.91)	(0.93)	(0.03)	(–2.15)
RESNA	0.0013	0.0012	0.0012	0.0010	0.0007	0.0010
	(2.18)	(1.90)	(2.43)	(1.67)	(1.51)	(2.13)
BM	0.0037	0.0045	0.0039	0.0047	0.0038	0.0030
	(1.55)	(2.00)	(2.64)	(2.23)	(2.85)	(2.15)

uncertainty about a company's fundamentals, systematic risk, and idiosyncratic risk. Furthermore, the results suggest that the link between disagreement and return continuation is not subsumed by arbitrage risk or short-sale constraints.

The findings in this paper support the theoretical models linking disagreement to price drift and suggest that, besides measures of visibility, investor uncertainty, and information precision, heterogeneity of beliefs is an important determinant of return continuation.

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