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Divergence of Opinion and Equity Returns

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Abstract

In this paper, we examine the relation between stock returns and analysts' heterogeneous expectations. We find that stock returns are positively associated with divergence of opinion. Our evidence provides no support for Miller's (1977) overvaluation hypothesis, which predicts lower (higher) future returns for high (low) divergence of opinion stocks in the presence of short-selling constraints. Our findings are based on the use of the diversity measure, which is free from the confounding effects of uncertainty in analysts' forecasts and is therefore a more accurate measure of divergence of opinion than dispersion. Our results refute the view that dispersion in analysts' forecasts reflects divergence of opinion. Our evidence is robust to the use of alternative measures of short-selling constraints, time intervals, optimism in analysts' forecasts, and herding in analysts' behavior.

I. Introduction

Unlike conventional asset pricing models that rely on the assumption of homogeneous expectations, the more recent literature emphasizes the importance of heterogeneous investor expectations suggesting that divergence of opinion proxies for risk (see Williams (1977), Mayshar (1983), Epstein and Wang (1994), Merton (1987), and Varian (1985)). This research suggests that the greater the disagreement among investors about the value of a stock, the lower its market price relative to its true value and, therefore, the higher its future return. We refer to this as the divergence of opinion discount hypothesis. The key assumption in these models is that markets are frictionless and consequently short selling is unrestricted. In a different context, but consistent with the divergence of opinion discount hypothesis, Barry and Brown (1985) argue that securities for which there is relatively little information (i.e., small capitalization firms) are riskier due to greater parameter uncertainty (or estimation risk). In this framework, limited (or poor) information restricts the ability of investors to form return expectations

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with high confidence and therefore increases expected stock returns.[1] The limited information hypothesis is not at variance with the divergence of opinion discount hypothesis. It simply implies that divergence of opinion is likely to be exaggerated when there is little information available.

In contrast, Miller (1977) argues that, in the presence of market frictions, divergence of opinion among investors does not represent risk, and conjectures that it is priced at a premium. We refer to this as the divergence of opinion premium hypothesis. In Miller's world, when investors disagree on value, the most optimistic investors set stock prices.[2] Miller's hypothesis further implies that in the presence of short-sale constraints, divergence of opinion leads to higher security valuations and lower future returns.[3] It follows that, according to Miller, the negative relation between investor disagreement and future stock returns is more (less) pronounced when the short-sale constraint becomes more (less) binding.

In a recent study, Diether, Malloy, and Scherbina (2002) find that stocks with higher dispersion in analysts' earnings forecasts earn lower future returns than otherwise similar stocks. In view of that evidence, they argue that these findings are consistent with the prediction of Miller's "premium" theory and that differences in analysts' forecasts (dispersion), as a proxy of divergence of opinion, do not represent risk.[4] Then again, if dispersion in analysts' forecasts proxies risk arising from the informational uncertainty of the firm, the dispersion anomaly in returns of Diether et al. (2002) implies that investors desire more risk, not less. In contrast, Cragg and Malkiel (1968), (1982), Friend, Westerfield, and Granito (1978), and Harris (1986) provide some evidence in favor of a positive association between future stock returns and dispersion in analysts' earnings forecasts. These studies, however, rely on small datasets that do not allow broad inferences to be drawn. Boehme, Danielsen, and Sorescu (2006), using trading volume (turnover), a somewhat controversial measure of differences in opinion (Jones, Kaul, and Lipson (1994)), as a proxy for differences of opinion find that highly short-sale constrained stocks with the highest turnover realize low future returns consistent with Miller's prediction. However, they also find the same result even for stocks with the lowest turnover, which is at variance with Miller's hypothesis.[5] While

[1]For an explanation of the small firm effect based on the limited information as a distinct source of risk, see also Barry and Brown (1984), (1986). The analytical work of Easley and O'Hara (2004) also predicts higher expected returns for firms with limited information (i.e., higher information risk).

[2]Diamond and Verrecchia (1987), however, argue that when short selling is costly it signals greater negative aggregate information that negates Miller's "premium."

[3]In sharp contrast with the frictionless world of Merton (1987) and Varian (1985), Miller (1977) assumes that the short-sale constraint is absolute in the sense that short selling is prohibited. In reality, however, short selling is neither frictionless nor prohibited.

[4]Using a large proprietary dataset consisting of 91,000 individual accounts in an S&P500 index fund, Goetzmann and Massa (2001) proxy divergence of opinion by the heterogeneity of trade among investor classes. They show that this proxy explains part of the stock returns that are not accounted for by standard asset pricing factors.

[5]Jones et al. (1994), argue that articles by Easley and O'Hara (1990) and Harris and Raviv (1993) that highlight the relation between stock-price dynamics and volume of trade as a proxy for differences of opinion, do not distinguish between volume (or size of trades) and frequency of trades, and therefore cannot explain why volume and frequency of trade have no information relevant to the pricing of stocks. On the contrary, Jones et al. (1994) find that transactions rather than volume and frequency of trades have information content. This could be a reason why volume per se may not capture differences of opinion. Moreover, trading volume may reflect investor overconfidence and disposition effects (Statman, Thorley, and Vorkink (2004)).

differences of opinion among investors are generally believed to play an important role in asset pricing, the conflicting theoretical predictions of divergence of investor opinion on asset prices remain an unresolved issue.[6] Surprisingly, there is very little evidence on how differences of opinion influence asset prices. Most importantly, the findings of this literature are contradictory. To our knowledge, this is the first study to examine the relation between divergence of opinion and future stock returns in the context of alternative and varying short-selling costs.

In this paper, we examine the relation between future stock returns and analysts' heterogeneous expectations. Unlike previous studies, we use Barron, Kim, Lim, and Stevens' (1998) (hereafter BKLS) approach of gauging analysts' divergent beliefs. We find a positive and significant association between future stock returns and divergence of opinion among analysts. We interpret this to be consistent with the divergence of opinion discount hypothesis. The results are robust to the severity of alternative short-sale constraints. Our evidence, however, provides no support for Miller's (1977) divergence of opinion premium hypothesis predicting lower (higher) future returns for high (low) divergence of opinion stocks in the presence of short-selling constraints.

This study contributes to the literature in several ways. First, our results indicate that differences of opinion have an important and significant impact on stock prices consistent with the prediction of the divergence of opinion discount hypothesis. We also find that small cap stocks (i.e., stocks with limited information) are subject to greater divergence of opinion realizing higher future returns. This evidence is consistent with the limited information theory of Barry and Brown (1984), (1985). Second, using the BKLS (1998) diversity in analysts' forecasts measure to capture divergence of opinion, we show that diversity is priced at a discount. Our findings are in line with the criticism of BKLS (1998), who argue that the dispersion in analysts' forecasts is a poor proxy of differences of opinion. Third, the empirical results fail to support Miller's view that divergence of opinion is priced at a premium and contradict the findings of Diether et al. (2002) who show a negative relation between dispersion in analysts' forecasts and future stock returns. Fourth, in contrast with Miller's (1977) overvaluation story, we find that stock overvaluation is associated with the presence of low differences of opinion among market participants. Finally, our results are robust to the use of alternative measures of short-selling constraints, time intervals, optimism of analysts' forecasts, and herding in analysts' behavior.

The rest of the paper is organized as follows. Section II illustrates the shortcomings of the existing empirical literature that examines the relation between divergence of opinion and future stock returns and summarizes the testable hypotheses of this study. Section III describes the diversity measure of BKLS (1998) as a proxy for divergence of opinion, variable definitions, data sources, and the sample selection. Section IV presents and describes the empirical results. Section V provides robustness tests. Section VI concludes.

[6] Doukas, Kim, and Pantzalis (2004) investigate a possible explanation of the value anomaly based on the divergence of opinion argument and show that differences of opinion explain the value premium anomaly.

II. Hypothesis Development

A. Empirical Literature Limitations

Previous studies that investigate the relation between divergence of opinion and future stock returns suffer from several limitations that raise serious concerns about the validity of their findings. First, from the literature on differences of opinion two pricing predictions emerge that depend on the nature of short-selling constraints. On the one hand, in the presence of divergence of opinion and less binding short-selling constraints, prices are less likely to reflect optimistic valuations since low short-selling costs allow greater participation in the market by pessimistic investors. On the other hand, in the presence of divergence of opinion and more binding short-selling constraints, prices are more likely to reflect optimistic valuations since pessimistic investors are kept out of the market by high short-selling costs. Hence, when the short-selling constraint becomes more (less) binding, high divergence of opinion stocks will realize lower (higher) future returns. Consequently, empirical tests attempting to discriminate between the two competing views on the relation between divergence of opinion and asset prices must control for i) the effects and ii) the severity of short-sale constraints. Unlike previous studies that investigate the effects of divergence of opinion by implicitly assuming that all firms are subject to the same short-sale constraint, our analysis is conducted by double sorting stocks on divergence of opinion and four alternative measures of short-selling constraints. This allows us to examine whether short-sale constraints have a bearing on the future returns of high (low) divergence of opinion stocks and whether their impact varies with the severity of the short-sale constraints.

Second, previous papers use the dispersion in analysts' forecasts to proxy for the differences in investors' beliefs. However, BKLS (1998) show that the dispersion in analysts' forecasts is likely to be a poor proxy for investor disagreement since it is contaminated by the effects of uncertainty in individual forecasts about the future payoffs of stocks. Consequently, it could be erroneous to rely on the dispersion in analysts' earnings forecasts measure as a proxy for divergence of opinion in order to assess its relation with stock returns. In view of that, the seemingly negative association between the dispersion in analysts' forecasts and ex post stock returns found by Diether et al. (2002) could be attributed to the effects of uncertainty in analysts' earnings forecasts. In fact, Pastor and Veronesi (2003) in an efficient market setting show that uncertainty about a firm's profitability results in lower future stock returns because firm value is a convex function of the firm's expected growth rate. In their model, an increase in uncertainty about the firm's expected growth rate leads to lower future stock returns because of Jensen's inequality.

In this paper, we show that the Diether et al. (2002) findings are reversed when we control for uncertainty in analysts' earnings forecasts. Specifically, we document that uncertainty has a negative association with future stock returns consistent with the prediction of Pastor and Veronesi's (2003) model. This evidence is also consistent with Jiang, Lee, and Zhang (2004) who show that high uncertainty stocks earn lower futures returns. We argue, then, that the study of Diether et al. (2002) establishes a negative association between future stock returns and uncertainty (dispersion), but not differences of opinion. The interpretation of their findings that the more investor views differ, the more stocks tend to be overpriced is erroneous, since their dispersion measure is driven by uncertainty in analysts' forecasts. Viewing equity as a call option provides a plausible explanation for the negative relation between uncertainty and returns. Consequently, from a contingent claims perspective, the results of Diether et al. (2002) do not represent a new puzzle (see also Johnson (2004)).

Furthermore, our study provides new evidence, based on BKLS's (1998) theoretically more sound and accurate measure of divergence of opinion, contradicting the findings of Diether et al. (2002).[7] In addition, we isolate the contaminating effects of uncertainty from divergence of opinion by employing an ex post uncertainty measure. Although an ideal test would require the use of ex ante measures to construct a trading rule, that is not the primary objective of this study. Instead, our focus is to shed light on the relation between disagreement and future stock returns by purging all contaminating effects. The ex post methodology is dictated by the lack of ex ante measures capturing the precision of analysts' common and idiosyncratic information.

Finally, we repeat this analysis for the 1998–2000 period that has been generally characterized as extremely optimistic (Schiller (2000)). Hence, this period provides a unique opportunity to reexamine whether divergence of opinion is priced at a premium or at a discount when the market is ex ante optimistic. Previous studies do not meet these requirements in testing the impact of divergence of opinion on stock returns. The conflicting theoretical views on whether divergence of opinion is priced at a premium or a discount, the inconclusive evidence, and the testing limitations of previous work have motivated this study.

B. Testable Hypothesis

The empirical work in this paper is motivated by the possible effects divergence of opinion may have on future stock returns. Specifically, we test the divergence of opinion discount hypothesis against the divergence of opinion premium hypothesis. The latter hypothesis is related to the theoretical work of Miller (1977) and predicts that i) high divergence of opinion stocks realize low future returns in the presence of short-selling constraints, and ii) future returns of high divergence of opinion stocks are even lower when the severity of short-selling constraints increases. The divergence of opinion discount hypothesis, however, predicts that differences of opinion increase expected stock returns.[8]

Therefore, we test whether there is a negative relation between investor disagreement and future stock returns. Additionally, we examine whether the negative relation between investor disagreement and future stock returns is more (less)

[7]While prior studies have used the dispersion in analysts' forecasts as a proxy for divergence of opinion (Diether et al. (2002), Ziebart (1990), and Atiase and Bamber (1994)) and for uncertainty (Imhoff and Lobo (1992), and Barron and Stuerke (1998)), BKLS (1998) show that dispersion is a function of diversity of opinion and uncertainty.

[8]In our context, differences of opinion stem from the volatility of a firm's underlying fundamentals rather than poor or limited information.

pronounced when the short-sale constraints become more (less) binding. Evidence in line with these predictions would support Miller's (1977) divergence of opinion premium hypothesis. However, evidence of a positive relation between investor disagreement and future stock returns would support the divergence of opinion discount hypothesis. Finally, we examine whether divergence of opinion has a distinct influence on the determination of asset returns. To conduct this test, we construct a divergence of opinion mimicking portfolio and investigate its impact on the cross section of stock returns.

III. Methodology

A. The Divergence of Opinion Measure and Variable Definitions

We aim at providing evidence on the relation between differences of opinion among security analysts and stock returns, accounting for the contaminating effects of the common and idiosyncratic elements of uncertainty in analyst information. Such a test would require ex ante measures to capture the precision of common and idiosyncratic information available to analysts (BKLS (1998)). Since there are no such ex ante measures, we use ex post measures.

Unlike previous studies that use the dispersion in analysts' earnings forecasts as a proxy for divergence of opinion among investors, we use the diversity measure of BKLS (1998).[9] BKLS show that forecast dispersion can be expressed as $D = V(1 - \rho)$, where V is uncertainty and $(1 - \rho)$ is diversity (disagreement) in analysts' information.[10] Therefore, dispersion in analysts' forecasts could be a poor proxy for investor disagreement since it is a function of both uncertainty and diversity. Diversity, $1 - \rho$, is defined as one minus the consensus (i.e., the degree of common beliefs among analysts), measured by the correlation in forecast errors across analysts. Because dispersion is jointly determined by uncertainty and diversity, it tends to understate the divergence of opinion among investors when there is uncertainty in analysts' forecasts about firms' future prospects. Previous studies using dispersion as a proxy for disagreement implicitly assume that V remains constant. However, since it is unlikely to be constant, the use of dispersion as a proxy for divergence of opinion could potentially lead to an erroneous interpretation of empirical results. We use the diversity measure as a proxy of divergence of opinion because it is unlikely to be contaminated by the effects of uncertainty in analysts' earnings forecasts. A detailed description of the estimation of $(1 - \rho)$ is shown in the Appendix. In summary, an important contribution of this study is the removal of the contaminating effects of uncertainty when examining the impact of differences of opinion on future stock returns.

The other variables used in the empirical analysis are defined as follows. Dispersion, D, is measured as the standard deviation of analysts' forecasts deflated

[9]The diversity measure of BKLS (1998) is also used in other studies (see Barron, Byard, and Kim (2002)).

[10]BKLS develop a model of how analysts' earnings forecasts are related to their general information environment, which consists of public (common) information and their own beliefs (idiosyncratic information).

by the absolute value of the mean forecast.[11] Returns, RET, are average monthly returns for equally weighted portfolios calculated over a one-year period starting from July of year t and ending with June of year $t + 1$. The book-to-market (BM) and SIZE (market value of common equity) measures are computed as in Fama and French (1996). Institutional shareholdings, measured as a percentage of total common shares outstanding in year t, IO, are from filings with the SEC in the first half of year t. We construct a short-selling costs index, SSCI, which is defined as $[(11 - \text{Rank SIZE}) + (11 - \text{Rank IO})]$, where Rank SIZE (Rank IO) takes values from one to 10 depending on which size (institutional shareholdings) decile the firm belongs to. Our short-selling costs index (SSCI) is using firm characteristics (i.e., firm size and IO) to proxy for the supply of stock that lenders can provide to short sellers as suggested by D'Avolio (2002). Relative short interest, RSI, is the percentage of each firm's outstanding shares held short in June each year. This is the short interest scaled by the firm's total number of outstanding shares in June of each year. The mean forecast error, MFE, is the difference between the average forecasted earnings per share, EPS, and the actual EPS, deflated by the absolute value of the mean forecast.

B. Data Sources and Sample Selection

This section describes the data sources and the sample selection. It also identifies the explanatory variables used in the empirical tests that follow. We use analyst forecast information included in the Institutional Brokers Estimate System (IBES) U.S. Detail History dataset.[12] We use individual analysts' forecasts issued in June or, if not available in June, forecasts issued in May or April and last confirmed as "recent" in June. For example, if the forecast was made in April or May and was last confirmed as recent in June, it will be used in our computation of averages and standard deviations for June. If an analyst makes more than one forecast from April to June, only the last forecast is used in our calculations. Each stock must be covered by at least two analysts, since we define dispersion as the standard deviation of earnings forecasts scaled by the absolute mean forecast.

To ensure that our results are not affected by the problems of the rounding procedure (i.e., rounding of forecasts and actual EPS estimates to the nearest penny (two decimal places)) and stock-split adjustments of IBES, which have plagued previous studies (see Payne and Thomas (2003)), we use the IBES Detail file. Rounding to the nearest penny is especially problematic because the IBES database may report a zero forecast error when in fact the forecast error is not zero. In addition, the rounding procedure tends to reduce the variation in forecasts across analysts resulting in a downward bias in forecast dispersion for firms with subsequent stock splits. Naturally, this bias increases with the number of stock splits. The data provided in the Detail file are rounded to one hundredth of one cent (i.e., four decimal places) and therefore the misclassification bias is

[11]We also obtain similar results when we construct the dispersion measure based on alternative deflators. We choose to present the absolute mean forecast deflated results in order to maintain comparability to the Diether et al. (2002) results.

[12]The use of the Detail History IBES data allows us to exclude outdated forecasts.

not severe.[13] We have also replicated our tests using the IBES Summary History dataset and obtained results similar to those reported here.

The returns data are from the Center for Research in Securities Prices (CRSP) Monthly Stocks Combined File, which includes NYSE, AMEX, and NASDAQ stocks. Book value data are from Compustat using book equity for the fiscal year-end. We retrieved the firm size (market value of common equity) data from CRSP as of the end of June each year. We followed the Fama and French (1993), (1996) procedure in constructing portfolios based on size rankings. Portfolios based on dispersion of analysts' forecast rankings are constructed annually using the information from the IBES datasets as indicated above. Reported portfolio returns are average monthly equally weighted returns computed over the annual period starting in the beginning of July of year t and ending at the end of June in year $t+1$.[14] The study covers the period from July 1983 through December 2001. The starting point for the study was determined by the availability of data in the IBES Detail History file. The intersection of the three datasets (IBES, CRSP, and Compustat) resulted in a sample that contains 35,782 firm-year observations. In addition, we use the Compustat Disclosure CD-ROMs to retrieve information on the percent of equity shareholdings by institutional investors. This information is not available for the years prior to 1987, so the sample of institutional shareholdings is smaller (28,297 firm-year observations). We use short interest for the month of June each year as an alternative short-sale constraint to control for the effects of short-selling costs. This information is obtained from NYSE and NASDAQ records starting in 1995. The part of our analysis that relies on short interest data makes use of a sample of 15,120 firm-year observations.

IV. Empirical Results

A. Descriptive Statistics and Sample Characteristics

Table 1 presents descriptive statistics for the stocks in our sample sorted on dispersion in analysts' earnings forecasts. The first row shows that, consistent with the findings of Diether et al. (2002), high dispersion stocks (Q5) earn lower future returns than low dispersion stocks (Q1). The return difference is statistically significant at the 1% level (with a t-value of 5.98).[15] High dispersion stocks (Q5) appear to have considerably higher BM ratios than low dispersion stocks (Q1). The BM difference between high and low dispersion stocks, Q5 − Q1, is 0.3069 and statistically significant at the 1% level (with a t-value of 22.12). Surprisingly, high dispersion stocks (Q5) earn a lower return than low dispersion

[13] In our sample, we identified only three firms (seven firm-year observations) with a cumulative adjustment split factor exceeding 100. Our results are not sensitive to the inclusion of these observations.

[14] Similar results are obtained using value-weighted portfolio returns. We report results based on equally weighted portfolios in order to maintain comparability with Diether et al. (2002).

[15] Our monthly return difference of −0.0041 translates into an annual return differential of about 4.92%. This is roughly half the size of the 9.48% annual return difference reported in Diether et al. ((2002), p. 2120). The higher return difference of Diether et al. can be attributed to the fact that: i) they use the Summary IBES data for computing dispersion, and ii) they rebalance dispersion-based portfolios on a monthly basis.

stocks (Q1) despite the fact that they have higher BM risk. This seems to contradict the BM premium effect documented in the literature in the sense that high dispersion stocks have high BM ratios and earn lower future returns than low dispersion stocks with low BM ratios.

Another interesting observation is that high dispersion stocks are more than three times smaller in size than low dispersion stocks. The size difference between these two groups of stocks is −2399.29 (with a t-value of −13.54). Furthermore, high dispersion stocks have considerably lower institutional ownership (IO) than low dispersion stocks suggesting that they are more difficult to short than low dispersion stocks. The IO difference between high and low dispersion stocks, Q5 − Q1, is −0.0787 (with a t-value of −18.35). Also, the cost of establishing short positions, as the SSCI illustrates, is significantly higher for high dispersion stocks (i.e., more difficult to short) than low dispersion stocks. This is also confirmed by the RSI measure, a widely used short-sale constraint proxy in previous studies.[16] The statistics show that the marginal cost of short selling is increasing with dispersion and it is considerably greater for high than for low dispersion stocks. The mean difference is 1.3541 and statistically significant at the 1% level (with a t-value of 10.38). This pattern indicates that high dispersion stocks are subject to greater short-selling costs and more likely to be held by investors that are more optimistic about their future prospects. The MFEs of high dispersion stocks prove that this is the case, as these stocks are found to be associated with higher MFEs than low dispersion stocks.[17] Finally, the last row in Table 1 indicates that diversity of opinion, based on the BKLS (1998) measure of divergence of opinion among investors, increases with dispersion in analysts' earnings forecasts.

B. Sorting by Dispersion and Alternative Measures of Short-Sale Constraints

Miller's divergence of opinion premium hypothesis predicts that in the presence of short-selling constraints i) high (low) divergence of opinion stocks earn low (high) future returns, and ii) the return difference between high dispersion and low dispersion stocks is higher when short-sale constraints are high than when short-sale constraints are low. We test Miller's predictions accounting for both the impact and the severity of short-selling constraints. Since stock returns are likely to be affected by short-sale constraints and their binding nature, we examine the impact of divergence of opinion on future stock returns by simultaneously sorting stocks on short-selling constraints and dispersion.[18] We control for the effects of short-sale constraints using four alternative proxies: SIZE, IO, SSCI, and RSI. To evaluate the severity of short-selling constraints, we examine whether the relation between stock returns and dispersion varies across different short-selling quintile categories.

[16]Originally proposed by Figlewski (1981). A rise in RSI indicates that the marginal cost of short selling is increasing (Boehme et al. (2006)).

[17]Diether et al. (2002) also show that optimistic forecasts are significantly associated with higher levels of dispersion in analysts' forecasts.

[18]See also Diamond and Verrecchia (1987), Asquith and Meulbroek (1998), and Desai, Ramesh, Thiagarajan, and Balachandaran (2002).

TABLE 1

Descriptive Statistics for Quintile Portfolios of Firms Sorted on Dispersion in Analysts' Forecasts

Table 1 reports the mean values and the number of firm-years for the different dispersion (D) in analysts' forecasts quintile portfolios and for the whole sample. Firms are assigned to the different portfolios on an annual basis after sorting on dispersion of analyst forecasts. The last column reports the mean difference between the highest and lowest quintiles and corresponding t-statistic. D is measured as the standard deviation of non-stale annual EPS forecasts issued in June, May, and April of year t, in that sequence, deflated by the absolute value of the mean forecast. The variables presented here are defined as follows: RET = average monthly return. Return period is from July of year t to June of $t+1$. BM = book-to-market, as in Fama and French (1996). SIZE = market value of common equity as of the end of June of year t. IO = institutional shareholdings as a percentage of total common shares outstanding as reported to the SEC in filings made in the first half of year t. SSCI = short-selling cost index = [(11 − Rank SIZE) + (11 − Rank IO), where Rank SIZE (Rank IO) takes values from 1 to 10 depending on which size (institutional shareholdings) decile the firm belongs to. RSI = relative short interest in June of year t as a percent of shares outstanding. MFE = mean forecast error, deflated by the absolute value of the mean forecast (as in Diether, Malloy, and Scherbina (2002)) $(1-\rho)$ = diversity of opinion measure, as in BKLS (1998). *,**,*** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dispersion (D)						
	Low (D) Q1	Q2	Q3	Q4	High (D) Q5	All Firms	Q5 − Q1 [t-statistic]
RET	0.0128 (7147)	0.0125 (7158)	0.0110 (7144)	0.0114 (7159)	0.0087 (7174)	0.0113 (35782)	−0.0041*** [−5.98]
BM	0.5265 (7147)	0.5771 (7158)	0.6256 (7144)	0.6974 (7159)	0.8334 (7174)	0.6521 (35782)	0.3069*** [22.12]
SIZE	3409.67 (7147)	3467.90 7158)	2570.06 (7144)	1905.46 (7159)	1010.38 (7174)	2471.70 (35782)	−2399.29*** [−13.54]
IO	0.4687 (5561)	0.4810 (5671)	0.4656 (5677)	0.4343 (5662)	0.3900 (5636)	0.4480 (28297)	−0.0787*** [−18.35]
SSCI	10.5314 (5651)	9.8856 (5671)	10.5198 (5677)	11.5150 (5662)	12.8854 (5636)	11.0653 (28297)	2.3540*** [27.22]
RSI	1.3984 (3051)	1.6584 (3074)	1.8021 (3043)	2.2229 (3003)	2.7525 (2949)	1.9604 (15120)	1.3541*** [10.38]
MFE	0.0525 (7147)	0.0502 (7158)	0.1014 (7144)	0.2196 (7159)	1.2188 (7174)	0.3291 (35782)	1.1663*** [18.62]
$(1-\rho)$	0.2380 (7057)	0.3689 (7155)	0.3949 (7140)	0.4405 (7150)	0.5066 (7136)	0.3901 (35638)	0.2686*** [37.25]

Previous research suggests firm size as a short-selling characteristic.[19] Since small capitalization stocks tend to be held primarily by individual investors, the supply of shortable shares for small firms should be low. Individual investors rarely lend their shares directly or indirectly and, as a result, the cost of shorting small capitalization stocks is higher than that of large capitalization stocks. Furthermore, outstanding shares of small firms are not necessarily floated since insiders may hold a considerable portion of the shares outstanding. Large capitalization firms, however, are held more widely, and so finding a lender of shares should be less difficult. Moreover, shares of small firms are less likely to be "on special" than those of large firms (Reed (2002)). Therefore, small firms are associated with a higher cost in borrowing and short selling. Finally, short selling involves search and bargaining costs (Duffie, Garleanu, and Pedersen (2003)). Search and bargaining costs are more likely to be higher in small firms than in large ones.

To distinguish between short-sale constrained and short-sale unconstrained stocks, we also use IO. D'Avolio (2002) shows that IO is the major determinant of the quantity of shares supplied and, therefore, the cost of borrowing should

[19]Firm size has been used as a short-sale constraint proxy in several previous studies (see, for example, Chen, Hong, and Stein (2002), and Diether et al. (2002)).

be less (more) expensive for stocks with high (low) IO. Gompers and Metrick (2001) report a strong relation between IO and liquidity. This suggests that the cost of trading large quantities of shares for stocks with high IO should be low. The search and bargaining cost for stocks with high IO is also expected to be low. Indeed, if several institutional investors are lending many shares, it should be less costly to locate them and competition should lower the cost of direct borrowing. Finally, derivative instruments, and in particular put options, an alternative method of creating short positions, are likely to be more often available for stocks with high levels of institutional shareholdings.[20] Therefore, stocks with low IO are subject to a higher short-selling cost and they should be associated with lower future returns.[21]

We also construct a SSCI, as an alternative short-selling restriction measure based on firm characteristics such as SIZE and IO. SSCI proxies for the supply of stock lenders can provide to short sellers, as suggested by D'Avolio (2002). Thus, SSCI attempts to capture the combined effect of size and institutional shareholdings on the supply of shares borrowed by short sellers.

RSI is one of the most common short-sale constraint proxies. As noted earlier, high RSI indicates high loan demand and therefore the level of short interest can be viewed as a proxy for the marginal cost of shorting a security (Chen et al. (2002), D'Avolio (2002), and Lamont and Thaler (2003)). This suggests that stocks with high (low) RSI will be subject to higher (lower) short-sale constraints.

To draw inferences about the average future returns of stocks in the presence of divergence of opinion, we assign stocks to portfolios sorted on dispersion in analysts' earnings forecasts and alternative measures of short-selling constraints such as SIZE, IO, SSCI, and RSI, respectively. These results are reported in Table 2. Panel A lists average monthly dispersion returns on size-sorted portfolios. High dispersion stocks (High (D)/Q5) are associated with significantly lower future returns than low dispersion stocks (Low (D)/Q1) across all size-sorted portfolios. The return difference between high (Q5) and low dispersion (Q1) stocks, listed in the last row, is negative and statistically significant in all quintile portfolios suggesting that low dispersion stocks earn substantially higher returns than high dispersion stocks when we control for size. These results are in line with the findings of Diether et al. (2002) who use size to control for the effects of short-sale constraints. If, however, small capitalization stocks are more short-sale constrained than large capitalization stocks, consistent with Miller's (1977) hypothesis, one would also expect the return difference between Q5 and Q1 for the small size portfolio, $((\text{Q5} - \text{Q1})/\text{Small SIZE})$, (-0.0040) to be considerably higher than the return spread between Q5 and Q1 for the large size portfolio, $((\text{Q5} - \text{Q1})/\text{Large SIZE})$, (-0.0043). This is not supported by the data, as the return difference between these two arbitrage portfolios is small.

Panel B in Table 2 presents average future returns for portfolios sorted on dispersion in analysts' earnings forecasts and IO. High dispersion stocks earn lower future returns than low dispersion stocks in the lowest two IO quintiles, where the short-sale constraint is more binding. However, the last row shows that

[20]Ofek, Richardson, and Whitelaw (2004) show that the violation of the put-call parity is strongly related to lending fees. Lending fees, however, are related to IO.

[21]See Chen, Hong, and Stein (2002) and Reed (2002).

the return difference between high and low dispersion stocks is statistically insignificant in most cases. Furthermore, if IO proxies for the difficulty of shorting stocks, it is expected that stocks with low IO (i.e., high short-selling cost) will be associated with lower future returns than higher IO stocks. The return difference between Q5 and Q1 for the low IO portfolio, (Q5 − Q1)/Low IO, is −0.0032 while for the high IO portfolio, (Q5 − Q1)/High IO, is 0.0013. While this seems

TABLE 2

Returns of Portfolios of Firms Sorted on Dispersion in Analysts' Forecasts (D) and Alternative Measures of Short-Selling Restrictions

Table 2 reports average monthly returns for portfolios of firms that belong to different combinations of dispersion (D) quintiles and quintiles sorted on four different measures of short-selling restrictions. The four alternative measures of short-selling restrictions are: SIZE (used in Panel A), IO (institutional ownership used in Panel B), SSCI (short-selling cost index used in Panel C), and RSI (relative short interest used in Panel D). Portfolio returns are average monthly returns over July of year t to June of year $t+1$ period. Portfolios are formed annually after sorting independently on i) D, computed as the standard deviation of non-stale annual EPS forecasts issued in June, May, and April of year t, in that sequence, deflated by the absolute value of the mean forecast, ii) SIZE based on the market value of common equity as of the end of June of year t, iii) IO based on the percentage of common shares owned by institutional investors as reported to the SEC in filings made in the first half of year t, iv) SSCI, which is computed as [(11 − Rank SIZE) + (11 − Rank IO), where Rank SIZE (Rank IO) takes values from 1 to 10 depending on which size (institutional shareholdings) decile the firm belongs to, and v) RSI, based on the short interest as percent of shares outstanding in June of year t. Table 2 also reports the mean difference tests among extreme portfolios (Q5 − Q1) and the corresponding t-statistics in brackets. *,**,*** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Average Monthly Returns of Portfolios of Firms Sorted Independently on Dispersion (D) and SIZE (N = 35,782)

Dispersion (D)	Small SIZE Q1	Q2	Q3	Q4	Big SIZE Q5	All Firms	Q5 − Q1 [t-statistic]
Q1 Low (D)	0.0130	0.0117	0.0126	0.0134	0.0135	0.0128	0.0005 [0.36]
Q2	0.0092	0.0134	0.0122	0.0128	0.0132	0.0125	0.0040*** [2.78]
Q3	0.0112	0.0095	0.0102	0.0118	0.0123	0.0110	0.0011 [0.72]
Q4	0.0140	0.0111	0.0120	0.0110	0.0102	0.0114	−0.0038* [−1.95]
Q5 High (D)	0.0090	0.0086	0.0070	0.0098	0.0092	0.0087	0.0002 [0.08]
All firms	0.0111	0.0107	0.0106	0.0119	0.0122	0.0113	0.0011 [1.37]
Q5 − Q1 [t-statistic]	−0.0040** [−2.12]	−0.0031** [−1.97]	−0.0056*** [−3.83]	−0.0036*** [−2.82]	−0.0043*** [−3.40]	−0.0041*** [−5.98]	

Panel B. Average Monthly Returns of Portfolios of Firms Sorted Independently on Dispersion (D) and Institutional Ownership (IO) (N = 28,297)

Dispersion (D)	Low IO Q1	Q2	Q3	Q4	High IO Q5	All Firms	Q5 − Q1 [t-statistic]
Q1 Low (D)	0.0106	0.0130	0.0130	0.0139	0.0115	0.0125	0.0009 [0.56]
Q2	0.0113	0.0105	0.0127	0.0135	0.0125	0.0122	0.0012 [0.75]
Q3	0.0069	0.0100	0.0130	0.0116	0.0117	0.0110	0.0048*** [2.69]
Q4	0.0109	0.0143	0.0129	0.0111	0.0108	0.0119	−0.0001 [−0.05]
Q5 High (D)	0.0074	0.0077	0.0116	0.0125	0.0128	0.0098	0.0054*** [2.66]
All firms	0.0092	0.0112	0.0127	0.0126	0.0118	0.0115	0.0026*** [3.28]
Q5 − Q1 [t-statistic]	−0.0032* [−1.65]	−0.0053*** [−2.84]	−0.0014 [−0.70]	−0.0014 [−0.84]	0.0013 [0.80]	−0.0027*** [−3.28]	

(continued on next page)

TABLE 2 (continued)

Returns of Portfolios of Firms Sorted on Dispersion in Analysts' Forecasts (D) and Alternative Measures of Short-Selling Restrictions

Panel C. Average Monthly Returns of Portfolios of Firms Sorted Independently on Dispersion (D) and Short-Selling Cost Index (SSCI) (N = 28,297)

Dispersion (D)	Low SSCI Q1	Q2	Q3	Q4	High SSCI Q5	All Firms	Q5 − Q1 [*t*-statistic]
Q1 Low (D)	0.0121	0.0139	0.0119	0.0117	0.0126	0.0125	0.0005 [0.31]
Q2	0.0131	0.0129	0.0119	0.0111	0.0116	0.0122	−0.0015 [−0.91]
Q3	0.0123	0.0134	0.0099	0.0085	0.0108	0.0110	−0.0015 [−0.75]
Q4	0.0111	0.0118	0.0101	0.0118	0.0141	0.0119	0.0030 [1.26]
Q5 High (D)	0.0123	0.0103	0.0116	0.0092	0.0086	0.0098	−0.0038 [−1.46]
All firms	0.0123	0.0127	0.0111	0.0105	0.0112	0.0115	−0.0011 [−1.16]
Q5 − Q1 [*t*-statistic]	0.0002 [0.14]	−0.0036** [−2.23]	−0.0003 [−0.20]	−0.0025 [−1.35]	−0.0040** [−2.01]	−0.0027*** [−3.28]	

Panel D. Average Monthly Returns of Portfolios of Firms Sorted Independently on Dispersion (D) and Relative Short Interest (RSI) (N = 15,120)

Dispersion (D)	Low RSI Q1	Q2	Q3	Q4	High RSI Q5	All Firms	Q5 − Q1 [*t*-statistic]
Q1 Low (D)	0.0183	0.0151	0.0140	0.0106	0.0012	0.0130	−0.0171*** [−6.27]
Q2	0.0164	0.0171	0.0163	0.0107	0.0012	0.0129	−0.0152*** [−5.86]
Q3	0.0167	0.015	0.0150	0.0084	0.0044	0.0119	−0.0123*** [−4.03]
Q4	0.0207	0.0182	0.0173	0.0116	0.0036	0.0138	−0.0171*** [−5.18]
Q5 High (D)	0.0134	0.0171	0.0148	0.0170	0.0044	0.0124	−0.0090*** [−2.94]
All firms	0.0172	0.0165	0.0155	0.0116	0.0033	0.0128	−0.0139*** [−10.52]
Q5 − Q1 [*t*-statistic]	−0.0049* [−1.83]	0.0020 [0.71]	0.0008 [0.30]	0.0064** [2.17]	0.0032 [0.98]	−0.0006 [−0.53]	

to be in line with Miller's hypothesis, which predicts that the return difference between high and low dispersion stocks will be higher when short-sale constraints are high than when short-sale constraints are low, the return difference between these two arbitrage portfolios is not statistically significant.

Panel C in Table 2 reports average returns for portfolios double sorted on dispersion in analysts' earnings forecasts and on the SSCI. The results show that low dispersion stocks do not systematically earn higher future returns than high dispersion stocks. Hence, this return difference fails to provide support for Miller's hypothesis. When the short-selling costs are at a high level (High SSCI/Q5), however, low dispersion stocks realize significantly higher future returns than high dispersion stocks. The return difference between these two portfolios is −0.0040 (with a t-value of −2.01) suggesting that when short selling becomes more costly high dispersion stocks tend to earn lower future returns. Finally, while the return difference between Q5 and Q1 for the high SSCI portfolio, (Q5−Q1)/High SSCI, is higher than that of the low SSCI portfolio, (Q5 − Q1)/Low SSCI, as predicted by Miller's hypothesis, it is not statistically significant.

Panel D in Table 2 shows the effect of RSI on dispersion portfolio returns. Consistent with Miller's hypothesis, one would expect a strong and negative relation between dispersion and stock returns when RSI increases.[22] This relation is not supported by the data. The return difference between high (Q5) and low dispersion (Q1) stocks, shown in the last row, is statistically significant only in the first (Low RSI/Q1) and the fourth RSI quintile portfolios. A more interesting pattern that emerges from this panel is that when short selling becomes more costly (i.e., the short-sale constraint becomes more binding (High RSI/Q5)) the low dispersion stocks portfolio (Low (D)/Q1) earns 0.0012 while the high dispersion stocks portfolio earns (High (D)/Q5) 0.0044. This return difference between these two portfolios is only 0.0032 and statistically insignificant (with a t-value of 0.98). Following Miller's hypothesis, one would expect the opposite result. That is, if high dispersion stocks are associated with higher recall costs, as D'Avolio (2002) suggests, and high short interest indicates high short-selling costs due to increasing borrowing demand by short sellers (pessimistic investors), the prices of high dispersion stocks should reflect more optimistic beliefs than the prices of low dispersion stocks, realizing lower future returns. Furthermore, the return difference between Q5 and Q1 for the high RSI portfolio, (Q5 − Q1)/High RSI, is 0.0032 while that of the low RSI portfolio, (Q5 − Q1)/Low RSI, is −0.0049. This result also refutes Miller's hypothesis.

Overall, the evidence from Table 2 demonstrates that when we control for the severity and the effects of the short-selling constraint, using four alternative short-selling constraint proxies, high dispersion stocks do not systematically earn lower future returns than low dispersion stocks. Moreover, the evidence is also inconsistent with Miller's other hypothesis, which predicts that the greater the severity of short-sale constraints, the higher the future return difference between high and low dispersion stocks.

C. Is Dispersion in Analysts' Forecasts a Good Proxy for Divergence of Opinion?

Since BKLS (1998) argue that uncertainty in analysts' forecasts (V) might contaminate the dispersion measure, the results of Table 2 should be interpreted with caution. Under efficient market conditions, Pastor and Veronesi (2003) illustrate that uncertainty about a firm's growth prospects is associated with lower future stock returns due to Jensen's inequality because firm value is a convex function of its expected growth rate. Hence, if uncertainty plays an important role in the determination of dispersion, it is necessary to control for its potential influence on dispersion before we draw any inferences about the relation between differences of opinion and stock returns. To the extent that uncertainty has a marginal impact on dispersion, portfolios sorted on dispersion and uncertainty should gen-

[22]D'Avolio (2002) notes that another element of short-selling constraints is the expected cost of recall. He argues that difference in opinion increases the probability of recall and hence the cost of short selling. This could be a more important factor than loan fees in explaining why short sellers are reluctant to exploit the return difference between high and low dispersion stocks.

erate similar results to those reported in Table 2. Consequently, if dispersion portfolio returns fail to remain unchanged when we control for uncertainty, the diversity $(1 - \rho)$ measure of BKLS (1998) should be used in the analysis as the more appropriate measure of investor disagreement. To examine how sensitive the previous results are to uncertainty in analysts' forecasts, we estimate portfolio returns after sorting independently on dispersion, short-selling constraints, and uncertainty.

As before, we concentrate on the future return difference between high (top 30th percentile) and low (bottom 30th percentile) dispersion stocks. If dispersion is a clean measure of divergence of opinion, this return difference should continue to be negative and statistically significant across all three different states of uncertainty in analysts' forecasts (i.e., low V, medium V, and high V), controlling for the effects of short-selling constraints. Table 3 presents the returns on quintile dispersion portfolios sorted on uncertainty and four alternative short-selling constraints. These results are inconsistent with the predictions of Miller's theory. In contrast to the findings of Table 2 and, in particular, to the evidence of Diether et al. (2002), the return difference between high and low dispersion stocks, $((\text{high}) - (\text{low}))$, reported in the last row of Table 3, is positive and statistically significant for most portfolios. These findings suggest that when we control for uncertainty in analysts' forecasts, high dispersion stocks earn higher future returns than low dispersion stocks. This reverse pattern of dispersion returns is consistent with the claim of BKLS (1998) that dispersion manifests uncertainty in analysts' forecasts. These findings suggest that dispersion in analysts' forecasts is a poor proxy for divergence of opinion and, therefore, we employ the diversity of opinion measure $(1 - \rho)$ of BKLS (1998) in our analysis.

Another interesting result that emerges from Table 3 is the strong negative association between uncertainty and returns. This highlights the source of the anomaly in dispersion returns of Diether et al. (2002). This result is consistent with the prediction of Pastor and Veronesi (2003) and the findings of Jiang et al. (2004). Viewing equity as a call option, the negative relation between uncertainty and returns suggests that asset values increase with uncertainty. Therefore, the results of Diether et al. (2002) are in line with the prediction of the contingent claims theory rather than the overvaluation and costly arbitrage theories. The results of Table 3 are also consistent with Johnson's (2004) contingent claims interpretation of the Diether et al. (2002) results.[23]

D. Sorting by Diversity of Opinion and Alternative Measures of Short-Sale Constraints

In this section, we examine the association between stock returns and diversity of opinion in analysts' forecasts $(1 - \rho)$, as a proxy for divergence of opinion. If the diversity measure, as argued in BKLS (1998), depicts investor disagreement more accurately than the conventional measure of dispersion in analysts' forecasts used in previous studies, we expect to find stronger results. We first reproduce the

[23]Johnson (2004) uses dispersion as a proxy for idiosyncratic (parameter) risk and provides an explanation for the negative association between returns and dispersion from a contingent claims perspective.

tests of Table 2 by double sorting on diversity and alternative measures of short-selling constraints.[24] The results in Panel A of Table 4 provide support for the diversity return spread when SIZE is used to proxy for the short-sale constraint. In sharp contrast to the evidence reported in Panel A of Table 2, the new evidence shows that the average future return difference between high and low diversity portfolios, Q5 − Q1, is positive and statistically significant in all SIZE quintiles. These results contradict the findings of Diether et al. (2002) and suggest that disagreement of investor opinion is priced at a discount, not at a premium as Miller

TABLE 3

Returns of Portfolios of Firms Sorted on Dispersion in Analysts' Forecasts (D), Alternative Measures of Short-Selling Restrictions, and BKLS (1998) Uncertainty (V)

Table 3 reports average monthly returns for portfolios of firms that belong to different combinations of low/medium/high groups based on dispersion in analysts' forecasts (D), alternative measures of short-selling restrictions, and uncertainty in analysts' forecasts (V). The low (high) group includes the bottom (top) 30th percentile of firms ranked on a particular variable. The four alternative measures of short-selling restrictions are: SIZE (used in Panel A), IO (institutional ownership used in Panel B), SSCI (short-selling cost index used in Panel C), and RSI (relative short interest used in Panel D). Portfolio returns are average monthly returns over July of year t to June of year $t+1$ period. Portfolios are formed annually after sorting independently on i) (D) the dispersion of analyst forecasts, ii) (V) the analyst information uncertainty, and iii) alternative measures of short-selling constraints. These are: (a) SIZE based on the market value of common equity as of the end of June of year t, (b) IO based on the percentage of common shares owned by institutional investors as reported to the SEC in filings made in the first half of year t, (c) SSCI, computed as [(11 − Rank SIZE) + (11 − Rank IO), where Rank SIZE (Rank IO) takes values from 1 to 10 depending on which size (institutional shareholdings) decile the firm belongs to, and (d) RSI, based on the short interest as percent of shares outstanding in June of year t. The uncertainty measure (V) is computed as in BKLS (1998). D is computed as the standard deviation of non-stale annual EPS forecasts issued in June, May, and April of year t, in that sequence, deflated by the absolute value of the mean forecast. The table also reports the mean difference tests among extreme portfolios (High D − Low D) and the corresponding t-statistics in brackets. *,**,*** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Mean Monthly Returns for Portfolios of Firms Sorted Annually on Dispersion (D), SIZE, and Uncertainty (V) (N = 34,312)

	Small SIZE			Medium SIZE			Big SIZE		
	Low (V)	Med. (V)	High (V)	Low (V)	Med. (V)	High (V)	Low (V)	Med. (V)	High (V)
Low (D)	0.0160	0.0153	−0.0095	0.0156	0.0135	−0.0062	0.0148	0.0123	0.0018
Medium (D)	0.0195	0.0159	−0.0050	0.0156	0.0124	−0.0027	0.0165	0.0126	0.0041
High (D)	0.0296	0.0210	0.0046	0.0271	0.0160	0.0042	0.0115	0.0126	0.0069
All firms	0.0184	0.0178	0.0013	0.0158	0.0136	0.0012	0.0154	0.0125	0.0056
High − Low	0.0136***	0.0057**	0.0141***	0.0115***	0.0025*	0.0104***	−0.0033	0.0003	0.0051*
[t-statistic]	[2.89]	[2.24]	[4.32]	[2.67]	[1.78]	[4.38]	[−0.62]	[0.19]	[1.65]

Panel B. Mean Monthly Returns for Portfolios of Firms Sorted Annually on Dispersion (D), Institutional Ownership (IO), and Uncertainty (V) (N = 27,081)

	Low IO			Medium IO			High IO		
	Low (V)	Med. (V)	High (V)	Low (V)	Med. (V)	High (V)	Low (V)	Med. (V)	High (V)
Low (D)	0.0130	0.0133	−0.0108	0.0152	0.0150	−0.0046	0.0156	0.0117	−0.0100
Medium (D)	0.0151	0.0133	−0.0062	0.0181	0.0142	−0.0004	0.0173	0.0130	−0.0007
High (D)	0.0235	0.0168	0.0041	0.0315	0.0189	0.0053	0.0346	0.0178	0.0092
All firms	0.0143	0.0146	0.0007	0.0167	0.0157	0.0028	0.0164	0.0138	0.0041
High − Low	0.0105**	0.0036	0.0149***	0.0162***	0.0039**	0.0099***	0.0190***	0.0060***	0.0192***
[t-statistic]	[2.08]	[1.40]	[3.38]	[3.78]	[2.01]	[3.20]	[2.96]	[3.39]	[6.50]

(continued on next page)

[24]To account for the possibility that investors may be attracted to analysts with a superior forecasting record, we use an alternative diversity measure, which accounts for analysts' past forecasting ability. This measure is constructed using weights that are proportional to analysts' forecasting accuracy over the past four quarters. Our results are robust to the use of this weighted diversity measure.

TABLE 3 (continued)

Returns of Portfolios of Firms Sorted on Dispersion in Analysts' Forecasts (D), Alternative Measures of Short-Selling Restrictions, and BKLS (1998) Uncertainty (V)

Panel C. Mean Monthly Returns for Portfolios of Firms Sorted Annually on Dispersion (D), Short-Selling Cost Index (SSCI), and Uncertainty (V) (N = 27,081)

	Low SSCI			Medium SSCI			High SSCI		
	Low (V)	Med. (V)	High (V)	Low (V)	Med. (V)	High (V)	Low (V)	Med. (V)	High (V)
Low (D)	0.0153	0.0112	−0.0100	0.0144	0.0138	−0.0035	0.0154	0.0155	−0.0118
Medium (D)	0.0170	0.0138	0.0026	0.0168	0.0123	−0.0038	0.0175	0.0151	−0.0040
High (D)	0.0202	0.0157	0.0097	0.0318	0.0161	0.0058	0.0289	0.0203	0.0043
All firms	0.0159	0.0136	0.0053	0.0156	0.0136	0.0021	0.0169	0.0173	0.0013
High − Low	0.0049	0.0045**	0.0197***	0.0174***	0.0022	0.0094***	0.0135**	0.0048*	0.0161***
[*t*-statistic]	[0.75]	[2.42]	[6.66]	[3.94]	[1.31]	[3.22]	[2.43]	[1.83]	[4.12]

Panel D. Mean Monthly Returns for Portfolios of Firms Sorted Annually on Dispersion (D), Relative Short Interest (RSI), and Uncertainty (V) (N = 14,476)

	Low RSI			Medium RSI			High RSI		
	Low (V)	Med. (V)	High (V)	Low (V)	Med. (V)	High (V)	Low (V)	Med. (V)	High (V)
Low (D)	0.0177	0.0189	−0.0017	0.0162	0.0155	−0.0003	0.0094	0.0094	−0.0229
Medium (D)	0.0228	0.0181	0.0038	0.0187	0.0150	0.0023	0.0131	0.0086	−0.0088
High (D)	0.0359	0.0240	0.0120	0.0208	0.0205	0.0122	0.0555	0.0189	0.0023
All firms	0.0202	0.0200	0.0083	0.0173	0.0165	0.0082	0.0119	0.0120	−0.0024
High − Low	0.0182***	0.0051	0.0137**	0.0045	0.0049	0.0125**	0.0462***	0.0094***	0.0252***
[*t*-statistic]	[2.86]	[1.39]	[2.48]	[0.64]	[1.62]	[2.22]	[4.14]	[2.49]	[4.68]

(1977) suggests. Therefore, we interpret these results as being consistent with the view that divergence of opinion, using the BKLS (1998) diversity measure, represents risk.

In Panels B and C of Table 4, we replicate the above analysis after independently sorting stocks on diversity, IO, and SSCI, respectively, as alternative short-sale constraint proxies. As before, the results in the last row suggest that Q5 − Q1 returns are positive for all quintiles of IO and SSCI, respectively. Furthermore, these results are all statistically significant at the 1% level providing support for the view that divergence of opinion among market participants is viewed as risk. Once again, these results are inconsistent with those of Diether et al. (2002) suggesting that their findings are driven by the use of the dispersion in analysts' forecasts measure. These findings also fail to support Miller's hypothesis.

The results in Panel D of Table 4 provide further support that high divergence of opinion stocks earn higher returns than low divergence of opinion stocks even when we use RSI to proxy for the short-selling constraint. These results show that the return difference between high and low diversity portfolios, Q5 − Q1, is positive and statistically significant in all RSI quintiles. This is in sharp contrast with the evidence reported in Panel D of Table 2 where the return difference for the corresponding portfolios, based on dispersion rather than diversity, was mostly positive but not statistically significant. Thus, when we use the BKLS (1998) diversity measure to proxy divergence of opinion, which controls for uncertainty in analysts' earnings forecasts, we find that divergence of opinion is priced at a discount.

We also repeated the tests in Table 4 by excluding the returns in the month of the actual EPS announcements and in the adjacent months in order to examine whether our results are confined to the earnings announcement window where optimism or pessimism is revealed. These results are statistically indistinguishable from the ones reported here. In addition, tests using three- and six-month holding period return intervals produced somewhat stronger results than those reported in Table 4.

TABLE 4

Returns of Portfolios of Firms Sorted on Diversity in Analysts' Forecasts ($1-\rho$) and Alternative Measures of Short-Selling Restrictions

Table 4 reports average monthly returns for portfolios of firms that belong to different combinations of diversity in analysts' forecasts ($1-\rho$) quintiles and quintiles sorted on four different measures of short-selling restrictions. The four alternative measures of short-selling restrictions are: SIZE (used in Panel A), IO (institutional ownership used in Panel B), SSCI (short-selling cost index used in Panel C), and RSI (relative short interest used in Panel D). Portfolio returns are average monthly returns over July of year t to June of year $t+1$ period. Portfolios are formed annually after sorting independently on i) ($1-\rho$), the diversity measure as in BKLS (1998), ii) SIZE based on the market value of common equity as of the end of June of year t, iii) IO based on the percentage of common shares owned by institutional investors as reported to the SEC in filings made in the first half of year t, iv) SSCI computed as [(11 − Rank SIZE) + (11 − Rank IO)], where Rank SIZE (Rank IO) takes values from 1 to 10 depending on which size (institutional shareholdings) decile the firm belongs to, and v) RSI based on the short interest as percent of shares outstanding in June of year t. It also reports the mean difference tests among extreme portfolios (Q5 − Q1) and the corresponding t-statistics in brackets. *,**,*** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Average Monthly Returns of Portfolios of Firms Sorted Independently on Diversity ($1-\rho$) and SIZE (N = 34,957)

Diversity ($1-\rho$)	Small SIZE Q1	Q2	Q3	Q4	Big SIZE Q5	All Firms	Q5 − Q1 [t-statistic]
Q1 Low ($1-\rho$)	0.0025	0.0017	0.0036	0.0077	0.0058	0.0035	0.0033 [1.42]
Q2	0.0091	0.0117	0.0105	0.0112	0.0113	0.0108	0.0022 [1.26]
Q3	0.0168	0.0130	0.0126	0.0123	0.0129	0.0134	−0.0039** [−2.50]
Q4	0.0170	0.0158	0.0126	0.0125	0.0133	0.0142	−0.0037** [−2.43]
Q5 High ($1-\rho$)	0.0168	0.0145	0.0138	0.0134	0.0139	0.0144	−0.0029* [−1.91]
All firms	0.0110	0.0106	0.0107	0.0133	0.0123	0.0113	0.0013* [1.71]
Q5 − Q1 [t-statistic]	0.0143*** [7.81]	0.0128*** [8.23]	0.0102*** [6.82]	0.0056*** [4.01]	0.0081*** [5.57]	0.0109*** [15.31]	

Panel B. Average Monthly Returns of Portfolios of Firms Sorted Independently on Diversity ($1-\rho$) and Institutional Ownership (IO) (N = 27,705)

Diversity ($1-\rho$)	Low IO Q1	Q2	Q3	Q4	High IO Q5	All Firms	Q5 − Q1 [t-statistic]
Q1 Low ($1-\rho$)	0.0006	0.0055	0.0058	0.0058	0.0028	0.0040	0.0022 [1.04]
Q2	0.0077	0.0104	0.0120	0.0111	0.0137	0.0111	0.0059*** [3.36]
Q3	0.0126	0.0134	0.0141	0.0139	0.0135	0.0135	0.0009 [0.56]
Q4	0.0144	0.0150	0.0149	0.0156	0.0125	0.0145	−0.0019 [−1.07]
Q5 High ($1-\rho$)	0.0121	0.0131	0.0164	0.0152	0.0154	0.0144	0.0033** [2.02]
All firms	0.0091	0.0112	0.0126	0.0126	0.0119	0.0115	0.0028*** [3.42]
Q5-Q1 [t-statistic]	0.0115*** [5.74]	0.0076*** [4.05]	0.0106*** [5.34]	0.0094*** [5.53]	0.0128*** [7.72]	0.0104*** [12.45]	

(continued on next page)

TABLE 4 (continued)

Returns of Portfolios of Firms Sorted on Diversity in Analysts' Forecasts ($1-\rho$) and Alternative Measures of Short-Selling Restrictions

Panel C. Average Monthly Returns of Portfolios of Firms Sorted Independently on Diversity ($1-\rho$) and Short-Selling Cost Index (SSCI) ($N = 27,705$)

Diversity ($1-\rho$)	Low SSCI Q1	Q2	Q3	Q4	High SSCI Q5	All Firms	Q5 − Q1 [t-statistic]
Q1 Low ($1-\rho$)	0.0056	0.0072	0.0044	0.0032	0.0023	0.0040	−0.0033 [−1.24]
Q2	0.0146	0.0106	0.0099	0.0108	0.0103	0.0111	−0.0043** [−2.07]
Q3	0.0125	0.0141	0.0114	0.0133	0.0161	0.0135	0.0036* [1.91]
Q4	0.0128	0.0145	0.0137	0.0151	0.0166	0.0145	0.0037* [1.95]
Q5 High ($1-\rho$)	0.0141	0.0155	0.0152	0.0114	0.0155	0.0144	0.0014 [0.78]
All firms	0.0126	0.0127	0.0110	0.0104	0.0111	0.0115	−0.0015* [−1.73]
Q5 − Q1 [t-statistic]	0.0085*** [4.81]	0.0083*** [5.00]	0.0108*** [6.43]	0.0082*** [4.29]	0.0132*** [6.74]	0.0104*** [12.45]	

Panel D. Average Monthly Returns of Portfolios of Firms Sorted Independently on Diversity ($1-\rho$) and Relative Short Interest (RSI) ($N = 14,690$)

Diversity ($1-\rho$)	Low RSI Q1	Q2	Q3	Q4	High RSI Q5	All Firms	Q5 − Q1 [t-statistic]
Q1 Low ($1-\rho$)	0.0132	0.0134	0.0081	0.0020	−0.0109	0.0055	−0.0241*** [−8.03]
Q2	0.0175	0.0167	0.0154	0.0129	0.0022	0.0129	−0.0153*** [−4.85]
Q3	0.0189	0.0169	0.0156	0.0159	0.0050	0.0146	−0.0139*** [−4.99]
Q4	0.0195	0.0174	0.0198	0.0158	0.0078	0.0159	−0.0118*** [−3.91]
Q5 High ($1-\rho$)	0.0180	0.0192	0.0178	0.0110	0.0110	0.0154	−0.0070** [−2.37]
All firms	0.0171	0.0167	0.0157	0.0117	0.0030	0.0128	−0.0142*** [−10.57]
Q5 − Q1 [t-statistic]	0.0048* [1.69]	0.0058** [1.96]	0.0097*** [3.14]	0.0090*** [3.08]	0.0219*** [6.91]	0.0099*** [7.33]	

Overall, these results are consistent with the divergence of opinion discount hypothesis of Williams (1977), Mayshar (1983), Merton (1987), Varian (1985), and Epstein and Wang (1994), who argue that divergence of opinion represents risk. Our findings, however, are in sharp contrast with the evidence of Diether et al. (2002) and Miller's divergence of opinion premium hypothesis.

E. Sorting by Diversity of Opinion, Book-to-Market, and Short-Sale Constraints

Next, we focus on the relation between diversity portfolios and future returns, controlling for BM effects.[25] The purpose of this test is to examine whether the pattern of previous returns is merely a manifestation of BM and short-selling constraint effects. To conduct this analysis, we sort portfolios independently on

[25]BM is defined as in Fama and French (1996). Also, sorting on BM is done using the NYSE breakpoints used by Fama and French (1996).

diversity $(1-\rho)$, BM, and alternative measures of short-selling constraints (SIZE, IO, SSCI, and RSI) on an annual basis.

Table 5 shows the average monthly future returns of these triple sorted portfolios. In all four panels, the return difference between high diversity (Q5) and low diversity (Q1) stocks, ((Q5) − (Q1)), reported in the last row of each panel, is positive and statistically significant at conventional levels. This positive and statistically significant return difference is the basis for the claim that high diversity of opinion represents risk and, therefore, it is priced at a discount. These results are consistent with our previous findings reported in Table 4. Furthermore, they are robust to the controls for the potentially confounding effects of BM and short-selling constrained effects. These new findings offer additional support for the hypothesis that divergence of opinion is priced at a discount.

TABLE 5

Returns of Portfolios of Firms Formed after Sorting on Diversity in Analysts' Forecasts $(1-\rho)$, Alternative Measures of Short-Selling Restrictions, and Book-to-Market (BM) Ratios

Table 5 reports average monthly returns for portfolios of firms that belong to different combinations of low/medium/high groups based on diversity in analysts' forecasts $(1-\rho)$, alternative measures of short-selling restrictions, and BM ratios. The low (high) group includes the bottom (top) 30th percentile of firms ranked on a particular variable. The four alternative measures of short-selling restrictions are: SIZE (used in Panel A), IO (institutional ownership used in Panel B), SSCI (short-selling cost index used in Panel C), and RSI (relative short interest used in Panel D). Portfolio returns are average monthly returns over July of year t to June of year $t+1$ period. Portfolios are formed annually after sorting independently on i) $(1-\rho)$, the diversity measure as in BKLS (1998), ii) SIZE based on the market value of common equity as of the end of June of year t, iii) IO based on the percentage of common shares owned by institutional investors as reported to the SEC in filings made in the first half of year t, iv) SSCI computed as [(11 − Rank SIZE) + (11 − Rank IO), where Rank SIZE (Rank IO) takes values from 1 to 10 depending on which size (institutional shareholdings) decile the firm belongs to, and v) RSI, based on the short interest as percent of shares outstanding in June of year t. $(1-\rho)$, the diversity measure, is computed as in BKLS (1998). BM ratios are computed as in Fama and French (1996). The table also reports the mean difference tests among extreme portfolios (High $(1-\rho)$ − Low $(1-\rho)$) and the corresponding t-statistics in brackets. *,**,*** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Mean Monthly Returns for Portfolios of Firms Sorted Annually on Diversity $(1-\rho)$, BM, and SIZE ($N = 34,957$)

Diversity $(1-\rho)$	Low BM			Medium BM			High BM		
	Small SIZE	Med. SIZE	Large SIZE	Small SIZE	Med. SIZE	Large SIZE	Small SIZE	Med. SIZE	Large SIZE
Low $(1-\rho)$	0.0005	0.0035	0.0092	0.0056	0.0072	0.0086	0.0066	0.0089	0.0087
Medium	0.0126	0.0105	0.0121	0.0151	0.0141	0.0136	0.0155	0.0140	0.0142
High $(1-\rho)$	0.0148	0.0124	0.0115	0.0159	0.0143	0.0151	0.0206	0.0155	0.0150
All firms	0.0085	0.0089	0.0113	0.0115	0.0122	0.0131	0.0133	0.0130	0.0134
High − Low	0.0143***	0.0089***	0.0022	0.0104***	0.0070***	0.0065***	0.0140***	0.0066***	0.0064***
[t-statistic]	[6.65]	[6.25]	[1.50]	[5.19]	[6.16]	[5.91]	[5.97]	[3.97]	[3.57]

Panel B. Mean Monthly Returns for Portfolios of Firms Sorted Annually on Diversity $(1-\rho)$, BM, and Institutional Ownership (IO) ($N = 27,696$)

Diversity $(1-\rho)$	Low BM			Medium BM			High BM		
	Low IO	Med. IO	High IO	Low IO	Med. IO	High IO	Low IO	Med. IO	High IO
Low $(1-\rho)$	−0.0011	0.0059	0.0082	0.0058	0.0091	0.0059	0.0091	0.0082	0.0054
Medium	0.0092	0.0123	0.0141	0.0145	0.0139	0.0140	0.0133	0.0145	0.0144
High $(1-\rho)$	0.0114	0.0127	0.0143	0.0123	0.0181	0.0134	0.0172	0.0180	0.0159
All firms	0.0064	0.0105	0.0125	0.0111	0.0137	0.0117	0.0130	0.0135	0.0124
High − Low	0.0126***	0.0068***	0.0060***	0.0065***	0.0090***	0.0075***	0.0081***	0.0098***	0.0105***
[t-statistic]	[5.19]	[3.86]	[3.65]	[3.32]	[5.67]	[5.05]	[2.94]	[4.38]	[4.18]

(continued on next page)

TABLE 5 (continued)

Returns of Portfolios of Firms Formed after Sorting on Diversity in Analysts' Forecasts $(1-\rho)$, Alternative Measures of Short-Selling Restrictions, and Book-to-Market (BM) Ratios

Panel C. Mean Monthly Returns for Portfolios of Firms Sorted Annually on Diversity $(1-\rho)$, BM, and Short-Selling Cost Index (SSCI) (N = 27,705)

Diversity $(1-\rho)$	Low BM			Medium BM			High BM		
	Low SSCI	Med. SSCI	High SSCI	Low SSCI	Med. SSCI	High SSCI	Low SSCI	Med. SSCI	High SSCI
Low $(1-\rho)$	0.0113	0.0044	−0.0004	0.0065	0.0076	0.0071	0.0048	0.0082	0.0086
Medium	0.0140	0.0108	0.0116	0.0139	0.0134	0.0154	0.0146	0.0131	0.0149
High $(1-\rho)$	0.0138	0.0129	0.0117	0.0140	0.0149	0.0162	0.0141	0.0147	0.0212
All firms	0.0133	0.0095	0.0072	0.0123	0.0122	0.0126	0.0123	0.0121	0.0143
High − Low	0.0025	0.0084***	0.0121***	0.0075***	0.0073***	0.0091***	0.0093***	0.0065***	0.0126***
[t-statistic]	[1.50]	[5.01]	[4.89]	[5.51]	[5.25]	[4.29]	[3.89]	[3.37]	[4.70]

Panel D. Mean Monthly Returns for Portfolios of Firms Sorted Annually on Diversity $(1-\rho)$, BM, and Relative Short Interest (RSI) (N = 14,690)

Diversity $(1-\rho)$	Low BM			Medium BM			High BM		
	Low RSI	Med. RSI	High RSI	Low RSI	Med. RSI	High RSI	Low RSI	Med. RSI	High RSI
Low $(1-\rho)$	0.0168	0.0116	−0.0081	0.0138	0.0104	0.0003	0.0154	0.0097	−0.0010
Medium	0.0197	0.0156	0.0056	0.0154	0.0156	0.0153	0.0158	0.0172	0.0119
High $(1-\rho)$	0.0188	0.0138	0.0099	0.0186	0.0166	0.0126	0.0207	0.0243	0.0162
All firms	0.0185	0.0139	0.0027	0.0158	0.0145	0.0104	0.0170	0.0174	0.0095
High − Low	0.0020	0.0022	0.0181***	0.0049*	0.0062***	0.0123***	0.0052	0.0147***	0.0172***
[t-statistic]	[0.53]	[0.86]	[5.67]	[1.78]	[2.70]	[3.48]	[1.20]	[3.74]	[4.59]

V. Robustness Tests

A. Multi-Factor Regression Analysis

If high divergence of opinion stocks earn higher returns than low divergence of opinion stocks because investors perceive them as riskier, time-series portfolios of high divergence of opinion stocks should be associated with higher returns relative to an explicit asset pricing model. Fama and French (1993) suggest that a three-factor model may explain the time series of stock returns. While several researchers argue that the size and BM factor-mimicking portfolios may not represent risk factors, we simply use the Fama-French model to assess whether high divergence of opinion stocks earn higher returns for bearing additional risk. The Fama-French three factors are the excess return on the value-weighted market portfolio, RMRF, the return on a zero investment portfolio subtracting the return on a large firm portfolio from the return on a small firm portfolio, SMB, and the return on a zero investment portfolio estimated as the return on a portfolio of high BM minus the return on a portfolio of low BM stocks, HML. To account for the medium-term continuation in stock returns documented in Jegadeesh and Titman (1993), we include a momentum factor, UMD, to the Fama-French model. The momentum factor is constructed using the procedure of Carhart (1997). UMD is the return difference between the return on a portfolio of past winners ($t-12$ to $t-2$) and a portfolio of losers ($t-12$ to $t-2$). We use the intercept from the time-series regressions of the arbitrage portfolio between high divergence of opinion stocks and low divergence of opinion stocks to measure whether high divergence of opinion stocks earn higher returns for bearing additional risk after we account for market, size, BM, and momentum effects. While the intercept in these regressions appears to be similar in spirit to Jensen's alpha in the context of the CAPM, which controls for size, BM, and momentum factors in addition to the overall market factor, we do not interpret it as a measure of portfolio performance attribution.

If high divergence of opinion trades at a premium (i.e., high divergence of opinion stocks underperform low divergence stocks), the alpha of the arbitrage portfolio should be negative and statistically significant. Conversely, if high divergence of opinion trades at a discount (i.e., high divergence of opinion stocks outperform low divergence stocks), the alpha of the arbitrage portfolio should be positive and statistically significant. The arbitrage portfolios are constructed as the difference in returns between the top and the bottom quintile portfolios of stocks ranked on analysts' divergence of opinion based on the analysts' diversity $(1 - \rho)$ measure of BKLS (1998). If the return difference between high and low divergence of opinion stocks is a manifestation of confounding effects (i.e., differences in market beta, size, BM, and momentum), the regression intercepts should be economically and statistically indistinguishable from zero.

The four-factor time-series regression results are presented in Table 6. The diversity portfolio regressions for both equally and value-weighted quintiles indicate that all intercepts, with the exception of low diversity stocks, are positive and statistically significant. This indicates that the four-factor model leaves a large portion of return variability unexplained. Furthermore, the results show that the magnitude of these intercepts is rising with increases in diversity of opinion. This pattern of alphas is inconsistent with the divergence of opinion premium hypothesis and suggests that divergence of opinion could play a distinct role in asset pricing. Most importantly, the intercept of the equally weighted arbitrage portfolio regression is 0.0100 and is statistically significant at the 1% level (with t-value of 8.91). Similarly, the intercept of the value-weighted arbitrage portfolio regression is 0.0066 and is highly statistically significant (with t-value of 4.26).

To examine whether divergence of opinion has a distinct and pervasive influence on the determination of asset returns, we construct a disagreement risk factor, DRF, in the spirit of Fama and French and examine its impact on the cross section of stock returns. The DRF is the difference between the returns of the portfolios consisting of the top 30% and bottom 30% of stocks ranked based on our measure of divergence of opinion (i.e., on diversity of analysts' forecasts).[26] It is interesting to note that the mean of the DRF factor is significantly different from zero.[27] If stock returns are systematically influenced by investors' differences of opinion (manifested in analysts' divergence of opinion), DRF should be priced in the asset pricing model used earlier. Specifically, we test the hypothesis that DRF is not priced (i.e., obtains a zero coefficient value) against the alternative that it is priced in the stock market.

[26]This risk metric is an expectational risk measure and does not rely on risk stability assumptions as do most other methods of deriving risk proxies.

[27]Using equally weighted portfolio returns, the DRF mean is 0.0090382 (i.e., 0.90% per month with t-value of 8.19). When we use value-weighted portfolio returns, the DRF mean is 0.0051744 (i.e., 0.52% per month with t-value of 3.80).

TABLE 6

Time-Series Tests of Four-Factor Models for Diversity in Analysts' Forecasts $(1-\rho)$ Quintiles and Arbitrage Portfolios

$$R_{Qj}(t) = a + b\text{RMRF}(t) + s\text{SMB}(t) + h\text{HML}(t) + m\text{UMD}(t) + e(t)$$
$$R_{\text{High}}(t) - R_{\text{Low}}(t) = a + b\text{RMRF}(t) + s\text{SMB}(t) + h\text{HML}(t) + m\text{UMD}(t) + e(t)$$

Table 6 reports OLS regression coefficients (heteroskedasticity-adjusted) and corresponding t-values (in parentheses). The sample includes 216 monthly observations spanning the July 1983–June 2001 period. The quintile diversity $(1-\rho)$ portfolios are formed after ranking stocks annually on analysts' divergence of opinion based on analysts' diversity $(1-\rho)$ measure of BKLS (1998). The diversity arbitrage portfolios are constructed as the difference in returns $(R_{\text{High}}(t) - R_{\text{Low}}(t))$ between the top and the bottom quintile portfolios. RMRF is the value-weighted market return (RM) minus the one-month Treasury bill rate (RF). SMB (small minus big) is the difference each month between the return on small and big firms, while HML (high minus low) is the monthly difference of the returns on a portfolio of high BM and low BM firms. UMD (up minus down) is the momentum factor computed on a monthly basis as the return differential between a portfolio of winners and a portfolio of losers. RMRF, HML, SMB, and UMD are extracted from Kenneth French's Website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/). $(1-\rho)$ is measured as in BKLS (1998) using non-stale annual EPS forecasts issued in June, May, and April, in that sequence. *,**,*** denote significance at the 10%, 5%, and 1% levels, respectively.

Variables	$R_{\text{Low}(1-\rho)}$	$R_{\text{Q2}(1-\rho)}$	$R_{\text{Q3}(1-\rho)}$	$R_{\text{Q4}(1-\rho)}$	$R_{\text{High}(1-\rho)}$	$R_{\text{High}} - R_{\text{Low}}$
Panel A. Equally Weighted Portfolio Returns						
Intercept	−0.0011	0.0051***	0.0077***	0.0086***	0.0089***	0.0100***
	(−0.84)	(6.00)	(8.38)	(9.26)	(8.82)	(8.91)
RMRF	1.1536***	1.1410***	1.1095***	1.1083***	1.0637***	−0.0900***
	(43.53)	(49.23)	(45.16)	(52.49)	(45.41)	(−3.70)
SMB	0.8091***	0.5543***	0.5014***	0.4957***	0.4885**	−0.3206***
	(14.85)	(13.05)	(10.50)	(13.73)	(11.01)	(−9.37)
HML	0.1511**	0.1694***	0.1634***	0.0895*	0.1141**	−0.0370
	(2.39)	(3.50)	(3.20)	(1.93)	(2.21)	(−0.87)
UMD	−0.3928***	−0.2845***	−0.2123***	−0.2166***	−0.1934***	0.1994***
	(−6.29)	(−7.31)	(−5.21)	(−4.88)	(−4.16)	(7.16)
R^2	0.9397	0.9570	0.9453	0.9543	0.9396	0.4362
Panel B. Value-Weighted Arbitrage Portfolio Returns						
Intercept	0.0004	0.0059***	0.0056***	0.0084***	0.0071***	0.0066***
	(0.37)	(7.24)	(8.18)	(7.33)	(7.41)	(4.26)
RMRF	1.1151***	1.0626***	1.0228***	0.9677***	1.0215***	−0.0937***
	(41.14)	(57.30)	(57.63)	(48.11)	(43.54)	(−2.78)
SMB	0.1552***	−0.0940***	−0.1058***	−0.2010***	−0.2342***	−0.3893***
	(3.54)	(−3.53)	(−3.11)	(−6.81)	(−6.44)	(−7.96)
HML	0.0089	−0.0174	−0.0593*	−0.1827***	0.0499	0.0410
	(0.16)	(−0.44)	(−1.73)	(−4.34)	(1.38)	(0.62)
UMD	−0.3467***	−0.1918***	−0.0689***	−0.1994***	−0.0845***	0.2622***
	(−12.05)	(−8.50)	(−3.04)	(−3.54)	(−2.68)	(5.92)
R^2	0.9047	0.9472	0.9593	0.9491	0.9260	0.3993

As expected, for both equally weighted and value-weighted returns, Table 7 shows that the high divergence of opinion portfolios (i.e., Q4$(1-\rho)$ and High$(1-\rho)$) load positively and statistically significant on DRF, while low divergence of opinion portfolios have negative and statistically significant loadings on DRF. The adjusted-R^2 values in these regressions range between 0.94 and 0.96 indicating that the five-factor model does capture most of the variation in average portfolio returns. These results are in agreement with our prior evidence indicating that DRF plays an important role in explaining average stock returns.

Finally, we estimate a cross-sectional time-series (random effects) regression of average monthly returns on divergence of opinion, short-selling constraints, and other firm characteristics to examine whether our previous results remain robust. Most importantly, we are interested in examining whether divergence of

TABLE 7

Time-Series Tests of Five-Factor Models for Diversity in Analysts' Forecasts $(1-\rho)$ Quintiles

$$R_{Qj}(t) \quad = \quad a + b\mathrm{RMRF}(t) + s\mathrm{SMB}(t) + h\mathrm{HML}(t) + m\mathrm{UMD}(t) + d\mathrm{DRF}(t) + e(t)$$

Table 7 reports OLS regression coefficients (heteroskedasticity-adjusted) and corresponding t-values (in parentheses). The sample includes 216 monthly observations spanning the July 1983–June 2001 period. The quintile diversity $(1-\rho)$ portfolios are formed after ranking stocks annually on analysts' divergence of opinion based on analysts' diversity $(1-\rho)$ measure of BKLS (1998). The diversity risk factor (DRF) is constructed as the difference in returns between the highest 30th percentile and the lowest 30th percentile $(1-\rho)$ portfolios. In Panel A, the returns of the diversity portfolios and the DRF are equally weighted, while in Panel B the corresponding returns are value-weighted. RMRF is the value-weighted market return (RM) minus the one-month Treasury bill rate (RF). SMB (small minus big) is the difference each month between the return on small and big firms, while HML (high minus low) is the monthly difference of the returns on a portfolio of high BM and low BM firms. UMD (up minus down) is the momentum factor computed on a monthly basis as the return differential between a portfolio of winners and a portfolio of losers. RMRF, HML, SMB, and UMD are extracted from Kenneth French's Website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/). $(1-\rho)$ is measured as in BKLS (1998) using non-stale annual EPS forecasts issued in June, May, and April, in that sequence. *,**,*** denote significance at the 10%, 5%, and 1% levels, respectively.

Variables	$R_{\mathrm{Low}(1-\rho)}$	$R_{\mathrm{Q2}(1-\rho)}$	$R_{\mathrm{Q3}(1-\rho)}$	$R_{\mathrm{Q4}(1-\rho)}$	$R_{\mathrm{High}(1-\rho)}$
Panel A. Using Equally Weighted Portfolio Returns and an Equally Weighted DRF					
Intercept	0.0047***	0.0064***	0.0071***	0.0064***	0.0056***
	(3.66)	(6.27)	(6.05)	(5.98)	(4.75)
RMRF	1.0929***	1.1275***	1.1157***	1.1059***	1.0984***
	(53.32)	(51.38)	(44.95)	(54.61)	(50.16)
SMB	0.6281***	0.5143***	0.5200***	0.5642***	0.5917***
	(13.14)	(10.94)	(9.19)	(14.48)	(11.43)
HML	0.1119**	0.1607***	0.1674***	0.1044**	0.1365***
	(2.06)	(3.39)	(3.29)	(2.22)	(2.66)
UMD	−0.2686***	−0.2571***	−0.2250***	−0.2636***	−0.2642***
	(−4.88)	(−6.72)	(−5.28)	(−5.70)	(−5.42)
DRF	−0.7239***	−0.1599***	0.0741	0.2741***	0.4129***
	(−11.06)	(−2.60)	(0.86)	(4.20)	(6.27)
R^2	0.9613	0.9584	0.9456	0.9585	0.9495
Panel B. Using Value-Weighted Portfolio Returns and a Value-Weighted DRF					
Intercept	0.0034***	0.0072***	0.0060***	0.0070***	0.0054***
	(3.41)	(9.67)	(8.99)	(6.01)	(6.01)
RMRF	1.0496***	1.0330***	1.0137***	0.9968***	1.0579***
	(44.82)	(53.29)	(56.11)	(55.92)	(47.00)
SMB	−0.0355	−0.1799***	−0.1322***	−0.1163***	−0.1282***
	(−0.77)	(−6.11)	(−3.49)	(−3.60)	(−3.03)
HML	−0.0451	−0.0417	−0.0668**	−0.1187***	0.0799**
	(−1.05)	(−1.13)	(−2.04)	(−4.31)	(2.23)
UMD	−0.2675***	−0.1561***	−0.0579**	−0.2346***	−0.1286***
	(−9.21)	(−6.85)	(−2.35)	(−4.25)	(−3.79)
DRF	−0.6355***	−0.2863***	−0.0881	0.2823***	0.3534***
	(−10.51)	(−4.65)	(−1.54)	(6.80)	(5.51)
R^2	0.9440	0.9570	0.9603	0.9593	0.9429

opinion exerts a distinct risk influence in the cross section of stock returns. The regression results, as shown in Table 8, confirm the positive relation between differences of opinion and future stock returns obtained earlier.[28] Hence, the higher returns of high divergence of opinion stocks documented in Table 6 represent compensation for bearing differences of opinion risk. This evidence provides ad-

[28]We obtain similar results using the Fama and MacBeth (1973) methodology. We have also estimated regressions using BM as a dependent variable instead of stock returns (in the spirit of Hong, Kubik, and Stein (2004)) and found consistent, but somewhat weaker, results with our stock return evidence. These results are available from the authors.

ditional support for the explanatory power of divergence of opinion in the cross section of stock returns.

On the whole, consistent with our previous evidence, the results in Tables 6, 7, and 8 corroborate that high divergence of opinion stocks realize higher future returns than low divergence of opinion stocks: that is, divergence of opinion is priced at a discount. This consistent pattern of returns between high and low divergence of opinion stocks supports the existence of a unique divergence of opinion effect in stock returns.

TABLE 8

Panel Data Regressions of Average Monthly Excess Returns on Diversity of Analyst Forecasts $(1 - \rho)$

Table 8 reports results of random effects regressions using annual data for three different models. The dependent variable is the average monthly excess return of firm i, computed as the average over a 12-month period for the difference of firm i's return and the risk-free rate. The independent variables are: $(1 - \rho)$, the diversity measure as in BKLS (1998); the natural logarithm of the BM ratio, ln(BM), computed by matching the book value of equity in the end of December of year $t - 1$ to the market value of common equity at the end of June of year t; the stock's beta, BETA, computed from the market model estimated over the past 60 months preceding June of year t; the short-term return of the stock, RET_0_-2, computed as the average monthly return of the firm's stock computed over the months of May and June of year t; the average monthly return over the 10 months prior to that, RET_-3_-12, i.e., average monthly return of the firm's stock computed over the months of July of year $t - 1$ and April of year t; the natural logarithm of size, ln(SIZE), based on the market value of common equity as of the end of June of year t; the institutional ownership, IO, based on the percentage of common shares owned by institutional investors as reported to the SEC in filings made in the first half of year t; the relative short interest, RSI, based on the short interest as percent of shares outstanding in June of year t. *,***,*** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variable	(1)	(2)	(3)
$(1 - \rho)$	0.0053***	0.0053***	0.0054***
	(11.42)	(9.44)	(5.73)
BETA	−0.0024***	−0.0017***	−0.0003
	(−5.19)	(−3.16)	(−0.40)
ln(BM)	0.0014***	0.0013***	0.0013***
	(13.09)	(10.17)	(6.28)
ln(SIZE)	−0.0017***	−0.0017***	−0.0009***
	(−12.45)	(−10.52)	(−3.98)
RET_0_-2	0.0097***	0.0101***	0.0110**
	(3.10)	(2.84)	(2.15)
RET_-3_-12	−0.0642***	−0.0756***	−0.1215***
	(−12.45)	(−12.89)	(−14.57)
IO		2.15×10^{-5}	3.12×10^{-5}
		(1.39)	(1.50)
RSI			−0.0011***
			(−11.94)
Year dummies	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes
R^2 (within)	0.1083	0.0889	0.1304
Wald χ^2	2511.21	1554.30	1042.63
[Prob > χ^2]	[0.0000]	[0.0000]	[0.0000]
Fraction of variance due to random effects (u_i)	0.3336	0.3207	0.2189
Total N	31,431	24,655	12,476
No. of firms	5,823	5,082	3,954

B. Divergence of Opinion and Analysts' Optimism

Analyst-based divergence of opinion measures, including the diversity of BKLS (1998) employed in our analysis, implicitly assume that analysts' forecasts mirror the information they possess in an unbiased way.[29] However, analysts' incentives and strategic concerns may influence their earnings forecasts (see Dugar and Nathan (1995)). Consequently, issuing optimistic forecasts may potentially have confounding effects on the diversity measure used as a proxy for divergence of opinion. Specifically, optimistic analysts' earnings forecasts could bias the diversity measure, $(1 - \rho)$, downward because they tend to inflate the magnitude of uncertainty (V) by increasing the forecast error. To examine whether our results are sensitive to the bias of analysts' forecasting, we keep in the sample only stocks with positive MFEs (MFE > 0) and sort portfolios independently on diversity $(1 - \rho)$ and MFE on an annual basis. If analysts' optimistic bias has a severe influence on the diversity measure, excluding from the original sample stocks with non-optimistic forecasts (MFE < 0) should yield results that are different from those reported earlier.

We replicate this analysis for the non-bubble period, 1981–1997, in order to draw further inferences about the sensitivity of our results. The optimistic bias for this period is expected to be less dramatic than that of the bubble period. Therefore, this test allows us to examine whether the positive and significant pattern of return spreads between high and low divergence of opinion stocks found earlier varies across time intervals that are characterized by different degrees of analysts' optimistic bias. If optimistic bias has no bearing on the diversity measure, our results should remain unchanged across different periods.

Finally, we repeat this analysis for the 1998–2000 period, which is generally believed to represent one of the most dramatic episodes of the asset pricing bubble in the financial history of the U.S. Analysts' earnings forecasts about future stock return payoffs during that period have been generally characterized as extremely optimistic (Schiller (2000)).[30] Furthermore, it has been argued that the practical difficulties of shorting stocks forced pessimistic investors to stay out of the market until March 2000, which caused stock prices to be set by optimists who overwhelmed the market (Ofek and Richardson (2003)). Naturally, this period provides a unique opportunity to reexamine whether divergence of opinion was priced at a premium or at a discount when the market was more optimistic than in previous years. Therefore, this test is also expected to shed light on whether the diversity measure is potentially sensitive to optimistic bias in earnings expectations in years of extreme optimism relative to the evidence based on our entire and pre-bubble sample periods. If, indeed, the results from this period are similar to the evidence of the other two sample periods, we could safely conclude that neither the diversity measure nor our previous findings are sensitive to optimistic bias in earnings expectations.

Table 9 reports the results. Panel A presents results using portfolios sorted on analysts' diversity measure $(1-\rho)$ of BKLS (1998) and analysts' MFEs for the entire sample period. Panel B reports results for the 1983–1997 pre-bubble period while Panel C presents results for the 1998–2000 bubble period. Two major

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[29]The dispersion in analysts' forecasts measure, used in past studies as a proxy for divergence of opinion, relies on the same assumption that analysts' forecasts are unbiased.

[30]The extraordinary rise of Internet stock prices during the 1998–2000 period and the price fall in March 2000 with a continued price decline throughout 2000 came to be known as the "Internet bubble."

results emerge from this table. First, as the All Firms column shows, high divergence of opinion stocks (Q5) earn a higher return than low divergence of opinion stocks (Q1). The return difference between high and low dispersion stocks ((Q5) − (Q1)) is 0.0202 and statistically significant (with a t-value of 22.87). A similar result is obtained in Panels B and C. The return spread between high and low diversity stocks ((Q5) − (Q1)) for the pre-bubble period is 0.0190 and

TABLE 9

Returns of Portfolios of Firms Sorted on Diversity in Analysts' Forecasts $(1 - \rho)$ and Forecast Optimism

Table 9 reports average monthly returns for portfolios of firms that belong to different combinations of diversity in analysts' forecasts $(1 - \rho)$ quintiles and quintiles sorted on analysts' optimistic (i.e., positive) mean forecast errors (MFE). Panel A reports the results of the analysis using the sample of optimistic forecasts from the entire study period (1983–2001), while Panel B reports the analysis for the subsample of the pre-bubble period (1983–1997), and Panel C repeats the analysis for the subsample of the bubble period (1998–2000). Portfolio returns are average monthly returns over July of year t to June of year $t + 1$ period. Portfolios are formed annually after sorting independently on $(1 - \rho)$ and MFE, the mean forecast error, deflated by the absolute value of the mean forecast. Forecast error is the difference between mean forecast and actual EPS. Mean forecast is computed from non-stale annual EPS forecasts issued in June, May, and April, in that sequence. $(1 - \rho)$, the diversity measure, as in BKLS (1998) using non-stale annual EPS forecasts issued in June, May and April, in that sequence. The table also reports the mean difference tests among extreme portfolios (Q5 − Q1) and the corresponding t-statistics in brackets. *,**,*** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Results Based on Entire Sample of Optimistic Forecasts (N = 20,861)

Diversity $(1-\rho)$	Low MFE Q1 [mean MFE = 0.0185]	Q2 [mean MFE = 0.0734]	Q3 [mean MFE = 0.1809]	Q4 [mean MFE = 0.4273]	High MFE Q5 [mean MFE = 2.8347]	All Firms	Q5 − Q1 [t-statistic]
Q1 Low $(1-\rho)$	0.0117	0.0075	−0.0023	−0.0055	−0.0151	−0.0073	−0.0268*** [−6.95]
Q2	0.0091	0.0050	0.0022	0.0006	−0.0055	0.0002	−0.0146*** [−3.06]
Q3	0.0065	0.0083	0.0058	0.0006	0.0031	0.0061	−0.0034 [−1.30]
Q4	0.0129	0.0101	0.0098	0.0100	0.0065	0.0103	−0.0064*** [−3.06]
Q5 High $(1-\rho)$	0.0133	0.0139	0.0147	0.0062	0.0028	0.0129	−0.0105*** [−3.41]
All firms	0.0124	0.0093	0.0054	0.0015	−0.0066	0.0044	−0.0030*** [−21.12]
Q5 − Q1 [t-statistic]	0.0016 [0.68]	0.0064** [2.30]	0.0169*** [7.34]	0.0117*** [4.14]	0.0179*** [3.62]	0.0202*** [22.87]	

Panel B. Results Based on the Pre-Bubble Period (1983–1997) Subsample (N = 17,839)

Diversity $(1-\rho)$	Low MFE Q1 [mean MFE = 0.0187]	Q2 [mean MFE = 0.0727]	Q3 [mean MFE = 0.1787]	Q4 [mean MFE = 0.4276]	High MFE Q5 [mean MFE = 2.9871]	All Firms	Q5 − Q1 [t-statistic]
Q1 Low $(1-\rho)$	0.0145	0.0095	0.0010	−0.0041	−0.0150	−0.0062	−0.0295*** [−7.52]
Q2	0.0129	0.0083	0.0041	0.0006	−0.0061	0.0012	−0.0190*** [−4.09]
Q3	0.0090	0.0051	0.0061	0.0058	0.0023	0.0063	−0.0067*** [−2.67]
Q4	0.0133	0.0088	0.0077	0.0090	0.0047	0.0097	−0.0086*** [−4.04]
Q5 High $(1-\rho)$	0.0143	0.0103	0.0137	0.0031	0.0020	0.0128	−0.0123*** [−3.86]
All firms	0.0136	0.0116	0.0060	0.0016	−0.0071	0.0048	−0.0207*** [−23.70]
Q5 − Q1 [t-statistic]	−0.0002 [−0.91]	0.0021 [0.41]	0.0127*** [5.70]	0.0072*** [2.59]	0.0171*** [3.37]	0.0190*** [21.77]	

(continued on next page)

TABLE 9 (continued)

Returns of Portfolios of Firms Sorted on Diversity in Analysts' Forecasts $(1-\rho)$ and Forecast Optimism

Panel C. Results Based on the Bubble (1998–2000) Period Subsample (N = 3,022)

Diversity $(1-\rho)$	Low MFE Q1 [mean MFE = 0.0175]	Q2 [mean MFE = 0.0772]	Q3 [mean MFE = 0.1932]	Q4 [mean MFE = 0.4254]	High MFE Q5 [mean MFE = 1.9380]	All Firms	Q5 − Q1 [*t*-statistic]
Q1 Low $(1-\rho)$	−0.0016	−0.0031	−0.0164	−0.0144	−0.0157	−0.0137	−0.0141 [−1.10]
Q2	−0.0142	−0.0091	−0.0090	0.0005	−0.0022	−0.0051	0.0120 [0.65]
Q3	−0.0045	0.0051	0.0043	0.0054	0.0073	0.0043	0.0118 [1.19]
Q4	0.0106	0.0083	0.0245	0.0142	0.0147	0.0136	0.0041 [0.49]
Q5 High $(1-\rho)$	0.0071	0.0265	0.0200	0.0221	0.0062	0.0136	−0.0009 [−0.10]
All firms	0.0057	0.0067	0.0018	0.0014	−0.0029	0.0026	−0.0086** [−2.51]
Q5 − Q1 [*t*-statistic]	0.0087 [1.17]	0.0297*** [2.70]	0.0365*** [4.61]	0.0365*** [3.54]	0.0218 [1.33]	0.0273*** [8.39]	

statistically significant (with a t-value of 21.77). A similar return pattern between high and low diversity stocks ((Q5) − (Q1)) is documented for the bubble period. This return spread is 0.0273 and statistically significant (with a t-value of 8.39). Second, this pattern of positive return difference between high and low divergence of opinion stocks is validated in quintile portfolios for the entire sample period, and pre-bubble and bubble periods. As shown in Panel A, the return spread between high and low divergence of opinion stocks is always positive and statistically significant with the exception of the first quintile (Q1). In general, an analogous pattern emerges in Panel B for the 1981–1997 period. The evidence from the 1998–2000 bubble period, shown in Panel C, provides additional support that these results are consistent with those obtained from the entire and the pre-bubble sample periods. Therefore, we conclude that analysts' optimistic bias has no confounding effects on the diversity measure and our results.

These findings are consistent with the hypothesis that divergence of opinion is priced at a discount, but are in sharp contrast to the prediction of Miller's overvaluation theory. The positive return difference between high and low divergence of opinion stocks suggests that high divergence of opinion stocks are undervalued relative to the low divergence of opinion stocks. Furthermore, these results contradict the findings of Diether et al. (2002), who show that high dispersion stocks tend to perform poorly. These findings also suggest that when pessimists are out of the market, due to short-sale restrictions and other reasons, high divergence of opinion stocks trade at lower prices than low divergence of opinion stocks. The pre-bubble and the 1998–2000 period results indicate that stocks for which analysts' forecasts were not widely dispersed (i.e., low divergence of opinion stocks) performed poorly. However, stocks for which analysts' forecasts were divergent performed better than stocks for which analysts' forecasts were not divergent.

C. Divergence of Opinion and Analysts' Herding

The tendency of analysts to herd also has the potential to have a confounding effect on the diversity measure as a proxy for divergence of opinion.[31] To examine whether our results are sensitive to analysts' herding, we exclude from the analysis stocks followed by analysts who exhibit herding behavior. To implement this test we construct a herding index based on previous work (Olsen (1996), De Bondt and Forbes (1999), and Kim and Pantzalis (2003)) that defines herding as excessive agreement among analysts coupled with large forecast errors. Consistent with this literature, the herding index is computed as the ratio of a stock's absolute forecast error decile ranking to its forecast dispersion decile ranking. Then, we exclude stocks that belong to the top quintile after sorting on our herding index. If our previous results are merely a manifestation of herding in analysts' forecasts, evidence based on this subsample that is free of analyst herding should produce different results. If the new results are similar to those reported earlier, we could infer that neither the diversity measure nor our previous findings are sensitive to herding.

Table 10 reports average monthly future returns for portfolios sorted on diversity $(1 - \rho)$ and four alternative short-selling constraints on an annual basis. These results are conditional on analysts' herding and short-selling constraints. Once again, these results show that the return spread between high and low divergence of opinion stocks is positive and statistically significant with the exception of the first quintile (Q1) in Panels C and D. This evidence is reliably consistent with our previous findings and demonstrates that analysts' herding has no confounding effects on the diversity measure. When we repeat the analysis for the subperiods 1981–1997 and 1998–2000, our results remain essentially the same.[32]

VI. Conclusion

In this paper, we examine whether divergence of opinion is priced at a premium or a discount. We find a positive and significant association between future stock returns and divergence of opinion among investors. We interpret this to be consistent with the predictions of models of Williams (1977), Mayshar (1983), Merton (1987), Varian (1985), and Epstein and Wang (1994) that divergence of opinion represents risk. Our results are robust to the severity of alternative short-sale constraints.

Our findings, however, do not support Miller's (1977) view that divergence of opinion is priced at a premium in the presence of short-sale constraints. Our evidence also suggests that stock overvaluation is associated with the presence of low differences of opinion among market participants. Moreover, our evidence contradicts the empirical findings of Diether et al. (2002), who use the dispersion in analysts' forecasts measure as a proxy for divergence of opinion and show that it is associated with equity overvaluation. We demonstrate that their findings

[31]Herding behavior among security analysts is the phenomenon of large forecast errors combined with an unusually high consensus in forecasts (De Bondt and Forbes (1999)).

[32]These results are available from the authors.

are reversed when we control for uncertainty in analysts' earnings forecasts, indicating that their dispersion results are driven by uncertainty. This also confirms BKLS (1998) who argue that dispersion is a poor proxy for divergence of opinion since it is affected by uncertainty in analysts' earnings forecasts.

TABLE 10

Returns of Portfolios of Firms Sorted on Diversity in Analysts' Forecasts $(1-\rho)$ and Alternative Measures of Short-Selling Restrictions Excluding Firms Exhibiting Analyst Herding

Table 10 reports average monthly returns for portfolios of firms that belong to different combinations of diversity in analyst forecasts $(1-\rho)$ quintiles and quintiles sorted on four different measures of short-selling restrictions. The analysis utilizes a sample that excludes firms with analysts exhibiting herding behavior. The firms excluded belong to the top quintile after sorting on a herding index. The herding index is computed as the ratio of the firm's absolute forecast error decile ranking to its forecast dispersion decile ranking. The four alternative measures of short-selling restrictions are: SIZE (used in Panel A), IO (institutional ownership used in Panel B), SSCI (short-selling cost index used in Panel C), and RSI (relative short interest used in Panel D). Portfolio returns are average monthly returns over the July of year t to June of year $t+1$ period. Portfolios are formed annually after sorting independently on i) $(1-\rho)$, the diversity measure, as in BKLS (1998), ii) SIZE based on the market value of common equity as of the end of June of year t, iii) IO based on the percentage of common shares owned by institutional investors as reported to the SEC in filings made in the first half of year t, iv) SSCI computed as [(11 − Rank SIZE) + (11 − Rank IO), where Rank SIZE (Rank IO) takes values from 1 to 10 depending on which size (institutional shareholdings) decile the firm belongs to, and v) RSI based on the short interest as percent of shares outstanding in June of year t. Also reported are the mean difference tests among extreme portfolios (Q5 − Q1) and the corresponding t-statistics in brackets. *,**,*** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Average Monthly Returns of Portfolios of Firms Sorted Independently on Diversity $(1-\rho)$ and Firm Size (SIZE) (N = 28,369)

Diversity $(1-\rho)$	Small SIZE Q1	Q2	Q3	Q4	Big SIZE Q5	All Firms	Q5 − Q1 [t-statistic]
Q1 Low $(1-\rho)$	0.0003	0.0013	0.0030	0.0083	0.0081	0.0032	0.0078*** [3.27]
Q2	0.0145	0.0127	0.0117	0.0126	0.0123	0.0127	−0.0022 [−1.23]
Q3	0.0170	0.0157	0.0127	0.0118	0.0138	0.0140	−0.0032* [−1.85]
Q4	0.0159	0.0147	0.0131	0.0138	0.0132	0.0139	−0.0027 [−1.61]
Q5 High $(1-\rho)$	0.0174	0.0151	0.0138	0.0133	0.0138	0.0147	−0.0036** [−2.07]
All firms	0.0115	0.0115	0.0110	0.0121	0.0126	0.0117	0.0011 [1.40]
Q5 − Q1 [t-statistic]	0.0170*** [8.27]	0.0138*** [7.88]	0.0108*** [6.80]	0.0053*** [3.45]	0.0057*** [3.64]	0.0115*** [3.64]	

Panel B. Average Monthly Returns of Portfolios of Firms Sorted Independently on Diversity $(1-\rho)$ and Institutional Ownership (IO) (N = 22,461)

Diversity $(1-\rho)$	Low IO Q1	Q2	Q3	Q4	High IO Q5	All Firms	Q5 − Q1 [t-statistic]
Q1 Low $(1-\rho)$	−0.0030	0.0063	0.0052	0.0043	0.0085	0.0041	0.0115*** [5.13]
Q2	0.0111	0.0131	0.0142	0.0140	0.0126	0.0130	0.0015 [0.79]
Q3	0.0136	0.0131	0.0146	0.0150	0.0143	0.0143	0.0007 [0.41]
Q4	0.0130	0.0132	0.0148	0.0157	0.0135	0.0141	0.0005 [0.26]
Q5 High $(1-\rho)$	0.0134	0.0135	0.0170	0.0143	0.0156	0.0147	0.0022 [1.16]
All firms	0.0093	0.0120	0.0131	0.0130	0.0130	0.0121	0.0037*** [4.14]
Q5 − Q1 [t-statistic]	0.0163*** [7.43]	0.0072*** [3.14]	0.0118*** [5.53]	0.0100*** [5.53]	0.0071*** [3.88]	0.0106*** [11.35]	

(continued on next page)

TABLE 10 (continued)

Returns of Portfolios of Firms Sorted on Diversity in Analysts' Forecasts ($1-\rho$) and Alternative Measures of Short-Selling Restrictions Excluding Firms Exhibiting Analyst Herding

Panel C. Average Monthly Returns of Portfolios of Firms Sorted Independently on Diversity ($1-\rho$) and Short-Selling Cost Index (SSCI) (N = 22,461)

Diversity ($1-\rho$)	Low SSCI Q1	Q2	Q3	Q4	High SSCI Q5	All Firms	Q5 − Q1 [t-statistic]
Q1 Low ($1-\rho$)	0.0130	0.0070	0.0030	0.0021	0.0012	0.0041	−0.0118*** [−4.26]
Q2	0.0123	0.0126	0.0128	0.0141	0.0132	0.0130	0.0009 [0.40]
Q3	0.0143	0.0141	0.0117	0.0141	0.0173	0.0143	0.0030 [1.40]
Q4	0.0129	0.0160	0.0133	0.0135	0.0149	0.0141	0.0020 [0.94]
Q5 High ($1-\rho$)	0.0139	0.0142	0.0163	0.0125	0.0162	0.0147	0.0023 [1.10]
All firms	0.0133	0.0131	0.0115	0.0112	0.0116	0.0121	−0.0017* [−1.70]
Q5 − Q1 [t-statistic]	0.0009 [0.49]	0.0072*** [3.79]	0.0133*** [7.17]	0.0104*** [5.10]	0.0150*** [6.75]	0.0106*** [11.35]	

Panel D. Average Monthly Returns of Portfolios of Firms Sorted Independently on Diversity ($1-\rho$) and Relative Short Interest (RSI) (N = 11,908)

Diversity ($1-\rho$)	Low RSI Q1	Q2	Q3	Q4	Q5	High RSI All Firms	Q5 − Q1 [t-statistic]
Q1 Low ($1-\rho$)	0.0149	0.0102	0.0074	0.0063	−0.0061	0.0062	−0.0210*** [−5.36]
Q2	0.0178	0.0154	0.0170	0.0170	0.0051	0.0146	−0.0127*** [−4.19]
Q3	0.0198	0.0198	0.0167	0.0146	0.0048	0.0151	−0.0150*** [−4.86]
Q4	0.0185	0.0186	0.0183	0.0165	0.0066	0.0157	−0.0119*** [−3.50]
Q5 High ($1-\rho$)	0.0181	0.0179	0.0190	0.0108	0.0124	0.0157	−0.0057* [−1.77]
All firms	0.0178	0.0164	0.0159	0.0130	0.0042	0.0135	−0.0136*** [−8.98]
Q5 − Q1 [t-statistic]	0.0032 [0.91]	0.0077*** [2.63]	0.0116*** [3.42]	0.0045* [1.94]	0.0185*** [4.99]	0.0094*** [6.24]	

We find that the diversity in analysts' forecasts measure of BKLS (1998), as a proxy for divergence of opinion among investors, has incremental value relative to the simple dispersion in analysts' forecasts measure on several grounds. Most importantly our results show that they are not sensitive to different time intervals, optimistic earnings expectations, and analysts' herding, reflecting the power of the diversity measure. Overall, we provide new evidence in support of the view that divergence of opinion is a salient stock characteristic that is priced at a discount. Our study sheds new light on the conflicting theoretical views about the workings of divergence of opinion in support of the claim that divergence represents risk.

Appendix. Estimation of the BKLS (1998) Diversity Measure

BKLS (1998) define dispersion, D, as

$$D = V(1-\rho), \tag{1}$$

where $1-\rho$ is diversity, ρ is a measure of the consensus (also the across-analyst correlation in forecast errors), and V is uncertainty.

ρ and V are calculated as

$$\rho = h/(h+s), \tag{2}$$

$$\mathrm{V} = \mathrm{D}/(1-\rho), \tag{3}$$

where h is precision of common information, and s is precision of idiosyncratic information.

h and s are calculated as

$$h = (\mathrm{SE} - (\mathrm{D/N}))/[(\mathrm{SE} - (\mathrm{D/N})) + \mathrm{D}]^2, \tag{4}$$

$$s = \mathrm{D}/[(\mathrm{SE} - (\mathrm{D/N})) + \mathrm{D}]^2, \tag{5}$$

where SE is the squared error in the mean forecast deflated by the absolute value of the actual fiscal year-end EPS, D is variance in forecasts deflated by the absolute value of the actual fiscal year-end EPS, and N is the number of forecasts.

References

Asquith, P., and L. K. Meulbroek. "An Empirical Investigation of Short Interest." Working Paper, Massachusetts Institute of Technology (1998).

Atiase, R. K., and L. S. Bamber. "Trading Volume Reactions to Annual Earnings Announcements—The Incremental Role of Predisclosure Information Asymmetry." *Journal of Accounting and Economics*, 17 (1994), 309–329.

Barron, O. E.; D. Byard; and O. Kim. "Changes in Analysts' Information around Earnings Announcements." *Accounting Review*, 77 (2002), 821–846.

Barron, O. E.; O. Kim; S. C. Lim; and D. E. Stevens. "Using Analysts' Forecasts to Measure Properties of Analysts' Information Environment." *Accounting Review*, 73 (1998), 421–433.

Barron, O. E., and P. S. Stuerke. "Dispersion in Analysts Earnings Forecasts as a Measure of Uncertainty." *Journal of Accounting, Auditing, and Finance*, 18 (1998), 235–270.

Barry, C. B., and S. J. Brown. "Differential Information and the Small Firm Effect." *Journal of Financial Economics*, 13 (1984), 283–294.

Barry, C. B., and S. J. Brown. "Differential Information and Security Market Equilibrium." *Journal of Financial and Quantitative Analysis*, 20 (1985), 407–422.

Barry, C. B., and S. J. Brown. "Limited Information as a Source of Risk." *Journal of Portfolio Management*, 12 (1986), 66–72.

Boehme, R. D.; B. R. Danielsen; and S. M. Sorescu. "Short-Sale Constraints and Overvaluation." *Journal of Financial and Quantitative Analysis*, 41 (2006), 455–488.

Carhart, M. M. "On Persistence in Mutual Fund Performance." *Journal of Finance*, 52 (1997), 57–82.

Chen, J., H. Hong, and J. C. Stein. "Breadth of Ownership and Stock Returns." *Journal of Financial Economics*, 66 (2002), 171–205.

Cragg, L., and B. Malkiel. "The Consensus and Accuracy of Some Predictions of the Growth of Corporate Earnings." *Journal of Finance*, 23 (1968), 67–84.

Cragg, J., and B. Malkiel. *Expectations and the Structure of Share Prices*. Chicago, IL: Univ. of Chicago Press (1982).

D'Avolio, G. "The Market for Borrowing Stock." *Journal of Financial Economics*, 66 (2002), 271–306.

De Bondt, W. F. M., and W. P. Forbes. "Herding in Analyst Earnings Forecasts: Evidence from the United Kingdom." *European Financial Management*, 5 (1999), 143–163.

Desai, H.; K. Ramesh; S. R. Thiagarajan; and B. V. Balachandaran. "An Investigation of the Informational Role of Short Interest in the Nasdaq Market." *Journal of Finance*, 57 (2002), 2263–2288.

Diamond, D. W., and R. E. Verrecchia. "Constraints on Short-Selling and Asset Price Adjustment to Private Information." *Journal of Financial Economics*, 18 (1987), 277–311.

Diether, K. B; C. J. Malloy; and A. Scherbina. "Differences of Opinion and the Cross Section of Stock Returns." *Journal of Finance*, 57 (2002), 2113–2141.

Doukas, J. A; C. Kim; and C. Pantzalis. "Divergent Opinions and Value Stock Performance." *Financial Analysts Journal*, 60 (2004), 55–64.

Duffie, D.; N. Garleanu; and L. Pedersen. "Modeling Sovereign Yield Spreads: A Case Study of Russian Debt." *Journal of Finance*, 58 (2003), 119–159.

Dugar, A., and S. Nathan. "The Effect of Investment Banking Relationships on Financial Analysts' Earnings Forecasts and Recommendations." *Contemporary Accounting Research*, 12 (1995), 131–160.

Easley, D., and M. O'Hara. "The Process Price Adjustments in Securities Markets." Working Paper, Cornell Univ. (1990).

Easley, D., and M. O'Hara. "Information and the Cost of Capital." *Journal of Finance*, 59 (2004), 1553–1583.

Epstein, L. G., and T. Wang. "Intertemporal Asset Pricing under Knightian Uncertainty." *Econometrica*, 62 (1994), 283–322.

Fama, E. F., and K. R. French. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics*, 33 (1993), 3–56.

Fama, E. F., and K. R. French. "Multifactor Explanations of Asset Pricing Anomalies." *Journal of Finance*, 51 (1996), 55–84.

Fama, E. F., and J. D. MacBeth. "Risk, Return and Equilibrium—Empirical Tests." *Journal of Political Economy*, 81 (1973), 607–636.

Figlewski, S. "The Informational Effects of Restrictions on Short Sales: Some Empirical Evidence." *Journal of Financial and Quantitative Analysis*, 16 (1981), 463–476.

Friend, E.; R. Westerfield; and M. Granito. "New Evidence on the Capital Asset Pricing Model." *Journal of Finance*, 33 (1978), 903–917.

Goetzmann, W. N., and M. Massa. "Heterogeneity of Trade and Stock Returns: Evidence from Index Fund Investors." ICF Working Paper No. 00-28, Yale Univ. (2001).

Gompers, P. A., and A. Metrick. "Institutional Investors and Equity Prices." *Quarterly Journal of Economics*, 116 (2001), 229–259.

Harris, M., and A. Raviv. "Differences of Opinion Make a Horse Race." *Review of Financial Studies*, 6 (1993), 473–506.

Harris, R. "Using Analysts' Growth Forecasts to Estimate Shareholder Required Rates of Return." *Financial Management*, 15 (1986), 58–67.

Hong, H.; J. D. Kubik; and J. C. Stein. "The Only Game in Town: Stock-Price Consequences of Local Bias." Working Paper, Harvard Univ. (2004).

Imhoff, E. A., and G. J. Lobo. "The Effect of Ex-Ante Earnings Uncertainty on Earnings Response Coefficients." *Accounting Review*, 67 (1992), 427–439.

Jegadeesh, N., and S. Titman. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *Journal of Finance*, 56 (1993), 699–720.

Jiang, G.; C. M. C. Lee; and G. Y. Zhang. "Information Uncertainty and Expected Returns." Working Paper, Cornell Univ. (2004).

Johnson, T. C. "Forecast Dispersion and the Cross-Section of Expected Returns." *Journal of Finance*, 59 (2004), 1957–1978.

Jones, C. M; G. Kaul; and M. L. Lipson. "Transactions, Volume, and Volatility." *Review of Financial Studies*, 7 (1994), 631–651.

Kim, C. F., and C. Pantzalis. "Global/Industrial Diversification and Analyst Herding." *Financial Analysts Journal*, 59 (2003), 69–79.

Lamont, O. A., and R. H. Thaler. "Can the Market Add and Subtract? Mispricing in Tech Stock Carve-Outs." *Journal of Political Economy*, 111 (2003), 227–268.

Mayshar, J. "On Divergence of Opinion and Imperfections in Capital Markets." *American Economic Review*, 73 (1983), 114–128.

Merton, R. "A Simple Model of Capital Market Equilibrium with Incomplete Information." *Journal of Finance*, 42 (1987), 483–510.

Miller, E. M. "Risk, Uncertainty and Divergence of Opinion." *Journal of Finance*, 32 (1977), 1151–1168.

Ofek, E., and M. Richardson. "DotCom Mania: The Rise and the Fall of Internet Stocks." *Journal of Finance*, 58 (2003), 1113–1138.

Ofek, E.; M. Richardson; and R. Whitelaw. "Limited Arbitrage and Short Sales Restrictions: Evidence from Options Markets." *Journal of Financial Economics*, 74 (2004), 305–342.

Olsen, R. A. "Implications of Herding Behavior on Earnings Estimation: Risk Assessment and Stock Returns." *Financial Analysts Journal*, 52 (1996), 37–41.

Pastor, L., and P. Veronesi. "Stock Valuation and Learning about Profitability." *Journal of Finance*, 58 (2003), 1749–1789.

Payne, J. L., and W. B. Thomas. "The Implications of Using Stock-Split adjusted I/B/E/S Data in Empirical Research." *Accounting Review*, 78 (2003), 1049–1067.

Reed, A. "Costly Short-Selling and Stock Price Adjustment to Earnings Announcements." Working Paper, Univ. of North Carolina at Chapel Hill (2002).

Schiller, R. J. *Irrational Exuberance*. Princeton, NJ: Princeton Univ. Press (2000).

Statman, M.; S. Thorley; and K. Vorkink. "Investor Overconfidence and Trading Volume." Working Paper, Santa Clara Univ. (2004).

Varian, H. R. "Divergence of Opinion in Complete Markets: A Note." *Journal of Finance*, 40 (1985), 309–317.

Williams, J. T. "Capital Asset Prices with Heterogeneous Beliefs." *Journal of Financial Economics*, 5 (1977), 219–239.

Ziebart, D. A. "The Association between Consensus of Beliefs and Trading Activity surrounding Earnings Announcements." *Accounting Review*, 65 (1990), 477–488.