Is Difference of Opinion among Investors a Source of Risk?

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Abstract

This paper examines the relationship between difference of opinion among investors and the return on Australian equities. The paper is the first to employ both dispersion in analysts' earnings forecasts and maximum share turnover as proxies for difference of opinion among investors. We also investigate whether difference of opinion can explain the value anomaly. Our findings show that (a) difference of opinion is negatively related to stock returns and (b) it cannot explain the value anomaly. Our findings are consistent with Diether, Malloy, and Scherbina (2002) and provide strong support for Miller (1977). We reject the risk-based argument advanced by Doukas, Kim and Pantzalis (2004).

JEL Classification: G10, G12, G15

Key Words: Multifactor Model, Difference of Opinion, Analysts' Earnings Forecasts, Maximum Share Turnover, Value Anomaly

1. Introduction

This paper empirically tests the relationship between difference of opinion among investors and stock returns by using analysts' earnings forecasts and maximum share turnover as proxies for difference of opinion. The paper is the first to employ multiple proxies and asks whether difference of opinion could be used to explain the value anomaly.

A large body of empirical research over the past two decades has provided evidence against the prediction of the traditional Capital Asset Pricing Model (CAPM). This previous work shows that the cross-section of expected stock returns is not sufficiently explained by their market betas. It is well documented that firm size (Banz, 1981), earnings yield (Basu, 1977), leverage (Bhandari, 1988) and the firm's book value of equity to its market value (Chan, Hamao, and Lakonishok, 1991) adequately explain the cross-section of average stock returns better than the beta of a stock. More recently, Diether, Malloy, and Scherbina (2002) document a new anomaly: that firms with more uncertain earnings do worse. These patterns are considered anomalies because they are not explained by the CAPM (Fama and French, 2006).

The strong performance of value stocks (with high book-to-market value of equity) and the poor performance of growth stocks (with low book-to-market value of equity) have generated a lot of research interest in the area of asset pricing. For instance, the rationalists argue that value stocks are fundamentally riskier than growth stocks, and hence the compensation for this higher risk is reflected by their higher returns (Fama and French, 1993). On the other hand, the behavioralists argue that value stocks outperform growth stocks because investors over-extrapolate past performance, which results in stock prices that are too high for growth firms and too low for value firms (DeBondt and Thaler, 1987 and Lakonishok, Shleifer, and Vishny, 1994).

Doukas, Kim, and Pantzalis (2002) challenge the errors-in-expectations view by advancing difference of opinion as a plausible explanation for the abnormal return on value stocks. However, Diether et al. (2002) document a negative relationship between difference of opinion and stock returns. They show that stocks with higher dispersion in analysts' forecasts earn lower future returns than otherwise similar stocks. They argue that dispersion in analysts' earnings forecasts cannot be treated as a proxy for risk. Their findings provide support for Miller (1977), who hypothesizes that the price of a stock is set by optimists, and thus may be well above the actual underlying value of the stock. Hence, the greater the difference of opinion for a particular stock, the more likely that it will be overpriced and thus experience negative returns.

More recently, Doukas, Kim, and Pantzalis (2004) document that dispersion in analysts' forecasts is considerably higher for high BV/MV stocks than for low BV/MV stocks. Their findings suggest that difference of opinion represents risk not captured by the CAPM model or by the multifactor model of Fama and French (1996). However, it is important to note that the evidence on whether difference of opinion represents risk is not only exiguous but mixed and inconclusive.

In addition, little empirical research has been conducted on how difference of opinion affects stock prices (Diether et al., 2002). Thus, our objective is to provide much needed out of sample evidence on the relationship between difference of opinion and stock returns. We do so by investigating the relationship between difference of opinion and stock returns for equities listed on the Australian Securities Exchange (ASX). In addition, we ask whether difference of opinion could be used to explain the value anomaly.

The value anomaly is still hotly debated in the asset pricing literature and little, if any, research on it has been published outside the US. Thus, our study not only furthers the current debate in asset pricing but contributes to the extant literature of asset pricing in Australia (see, for example, Halliwell, Heaney, and Sawicki, 1999; Faff, 2001; Gaunt, 2004, and Gharghori, Chan, and Faff, 2006).

We study the Australian market for several reasons. First, asset pricing research done in Australia shows that there is much left to explain in the cross-sectional variation in equity returns. Second, the Australian equity market is quite different from the US market. With over 1700 listed stocks and a market capitalization of $1220 billion[1], the Australian market is much smaller than the US market. Further, the Australian market consists of different compositions of industries compared to the US. For example, two-thirds of the stocks listed on the ASX are represented by financials and materials companies[2]. Another striking feature of the Australian market is the heavier weighting on mining and resource stocks compared to the US[3]. The different size and unique features of the Australian market provide an entirely different setting than the US market. By conducting this study outside the US we examine whether the results of Doukas et al. (2004) are generalisable to other markets.

Our study makes several contributions. First, we adopt an alternative proxy-maximum share turnover - for measuring difference of opinion among investors. We adopt this proxy because analysts' forecasts are biased toward large stocks, in that the analyst following for small stocks is thin or sometimes even non-existent. This results in an unrepresentative sample wherein the coverage for small stocks is limited. This problem was also faced by Hong and Stein (2000), Diether et al. (2002) and Doukas et al. (2004).[4]

Due to this sample bias, an unbiased alternative proxy for difference of opinion among investors is required. Prior research documents two alternative proxies: (1) share turnover and (2) breadth in mutual fund ownership. Due to data

[1] Source: Australian Stock Exchange (ASX) Website as of August 2006

[2] Source: ASX Website

[3] Source: Australian Financial Review

[4] As an example, Diether et al.'s (2002) sample covers only 40.5% of total stocks listed in CRSP.

limitations we employ maximum share turnover, advanced by Diether (2004) as a proxy for difference of opinion among investors. Following, Diether (2004), we define maximum share turnover as the average daily adjusted share turnover in the highest 5-day period during the past year, minus the average daily adjusted share turnover during the rest of the year, excluding a 5-day window before and a 5-day window after the 5-day maximum.

Second, besides running individual regressions to test the relationship between difference of opinion and stock returns, we also adopt the generalized method of moments (GMM) system regression approach. Specifically, we augment the system with five additional equations which enables us to estimate the factor premiums concurrently in the context of the overall system. Hence, the systems test that we employ presents a stronger test than the individual regressions, as it enables the estimation of the individual risk-premium for each risk factor of the asset pricing models.

Third, this paper contributes to the asset pricing literature by examining whether difference of opinion explains the value anomaly in Australia. By using the GMM system regression approach, the factor premiums for HML and the two alternative proxies for difference of opinion can be compared. By comparing the factor premium of HML to the factor premium of difference of opinion, we can ascertain whether difference of opinion does indeed explain the value anomaly.

The results of our individual regressions for the two proxies are similar in that the coefficient for the difference of opinion risk factor (henceforth DRF) is insignificant in almost all cases. Thus, it is our conjecture that the DRF is not useful in pricing assets. The GMM system regressions for both proxies provide similar results. Specifically, these results show that difference of opinion (proxied by dispersion in analysts' earnings forecasts and maximum share turnover) has a significant, negative factor premium. This implies that difference of opinion under both proxies has a negative relationship with stock returns. Thus, we challenge Doukas et al. (2004)

who document that difference of opinion proxies for risk and that it is priced in equity returns. We argue that instead of being priced, the negative factor premium implies that high-difference-of-opinion stocks underperform low-difference-of-opinion stocks. Our finding is consistent with Diether et al. (2002) and consequently provides support for Miller's (1977) model. Furthermore, the system regressions also show that difference of opinion does not explain the value anomaly. If it did, one would expect the estimated HML factor premium to decrease or lose its significance in the difference of opinion enhanced Fama-French model. However, the results show that the HML factor premium does not decrease even when the DRF is introduced into the model. Therefore, we posit that difference of opinion does not explain the value anomaly.

Despite employing maximum share turnover as a proxy in our study, the problem of sample bias also remains unresolved. This is because the results for the maximum share turnover proxy are significant only when we include stocks that trade for 245 days or more per year. The results become insignificant once we remove this requirement and include stocks that trade less frequently. The stocks that trade for 245 days or more per year are mainly large stocks, and this makes our sample unrepresentative. Moreover, this partitioning of stocks reduces our sample size. In particular, after deleting stocks that trade for less than 245 days a year, the average number of stocks in our sample decreases considerably.

The remainder of this paper proceeds as follows: Section 2 describes the data and sample characteristics. Section 3 presents the empirical findings, and section 4 concludes the paper.

2. Data and Methods

2.1 Data

Monthly stock returns, market capitalization, the value-weighted market index, and the risk-free rate are collected from the Australian Graduate School Management (AGSM) file. The risk-free return is proxied by the monthly return on the 13-week Treasury note. The market return is proxied by the value-weighted market index constructed from data for all companies in the AGSM file.

For the construction of the SMB and HML portfolios, yearly data for book equity are obtained from Aspect Financial[5]. The asset pricing tests are conducted over the period January 1990 to December 2005. One year of prior data is required for the formation of the SMB and HML portfolios. Hence, the data are collected for the period 1989-2005. Our measure of Book Equity, Net Tangible Assets, is equal to shareholder's equity less intangible assets[6].

In order to create the DRF, analysts' earnings forecasts are collected from the Institutional Brokers Estimate System (I/B/E/S) files. To be included in this study, each stock has to be covered by at least two analysts (see, for example, Diether et al., 2002 and Doukas et al., 2004,). If more than one forecast is made during a month by the same analyst, only the latest forecast is used. The analysts' earnings forecasts are used to compute the dispersion in analysts' forecasts measure (DISP). The DISP measure is equal to the standard deviation of the earnings forecasts at the end of the year; this is readily obtained from the I/B/E/S files. For the construction of the maximum share turnover proxy, the trading volume and issued shares data are obtained from the Securities Institute Research Centre of Asia-Pacific (SIRCA). The data for trading volume and issued shares are obtained for the period January 1989 to February 2005.

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[5] The Aspect Financial Database provides comprehensive coverage of financial data for companies listed on the ASX.

[6] Intangible assets include R&D expenditures.

2.1.1 Portfolio Construction

We follow the mimicking portfolio approach of Fama and French (1993) in constructing the SMB and HML portfolios, and Carhart (1997) in constructing the momentum portfolio. We construct an asset pricing model which augments the Fama-French (1993) three-factor model by applying Carhart's (1997) momentum factor and the difference of opinion risk factor (DRF). This model is consistent with that of Doukas et al. (2004).

The DRF is constructed as follows. First, the DISP measure is obtained for all stocks which have at least two analysts following them. The stocks are further sorted into three equally weighted DISP portfolios (Low, Medium, and High). Stocks are ranked in December of year t – 1 and placed into one of the three portfolios (based on DISP rankings) from January to December of year t. DRF is the difference, each month, between the equally-weighted returns on the high-DISP portfolio and the equally-weighted returns on the low-DISP portfolio. In other words, the DRF is constructed by ranking company-year observations according to their DISP values and forming two equally weighted return portfolios based on the top third and bottom third of DISP rankings (Doukas et al., 2004). Monthly returns are computed for these portfolios for the following 12 months. This process is repeated annually for the length of the sample period.

We also employ maximum share turnover as an alternative proxy for difference of opinion. Thus, a DRF is constructed using maximum share turnover, defined as trading volume divided by the total number of issued shares. Maximum share turnover is calculated for all stocks in December of year t – 1. It is defined as the average daily adjusted share turnover of the highest 5-day period during the past year minus the average daily adjusted share turnover during the rest of the year excluding a 5-day window before and a 5-day window after the 5-day maximum.[7]

[7] To mitigate the influence of thin trading, stocks that have traded for less than 245 days in the past year are removed from the sample.

Once maximum share turnover is determined, stocks are sorted into three equally-weighted portfolios (Low, Medium, and High) from January to December of year t. The returns are recorded each month for each of these three portfolios. DRF is the difference each month between the equally-weighted returns on the high maximum share turnover portfolio and the equally-weighted returns on the low maximum share turnover portfolio[8]. The portfolios are rebalanced annually. This method is consistent with the construction of the DRF using DISP.

2.1.2 Test Portfolios

All stocks are ranked according to size and also according to book-to-market in December of year t-1. Firms are then divided into five groups, and 25 portfolios are formed at the intersection of the five size groups and five book-to-market groups. The stocks remain in these portfolios from January to December of year t. The excess returns on these 25 portfolios are the value-weighted returns on each portfolio less the return on the risk-free asset.

2.2 Methodology

2.2.1 Individual Regressions

Our multi-factor model takes the following form:

$$R_{pt} – R_{ft} = a_{pt} + b_p RMF_t + s_p SMB_t + h_p HML_t + m_p MOM_t + d_p DRF_t + e_{pt} \qquad (1)$$

[8] The construction of DRF (maximum share turnover) is also done using monthly rebalancing. In the first instance, we do not skip a month between firm ranking and portfolio formation. Additionally, we construct DRF with a one-month lag between ranking and portfolio formation. The reason for recording returns with a one-month lag is to minimize the effect of bid-ask bounce and short-horizon return reversals (Lee and Swaminathan, 2000). The common practice of skipping a month between portfolio ranking and investment periods also avoids microstructure distortions (Griffin, Ji, and Martin, 2003). The results of the analysis obtained using these two alternative construction techniques are very similar to those obtained using annual rebalancing and thus have not been reported.

where

R_{pt} = Monthly return of a certain portfolio

R_{ft} = Risk-free return (return on the 13-week Treasury note at monthly intervals)

RMF_t = Monthly excess return of the value-weighted market portfolio

SMB_t = Monthly return on the mimicking portfolio for size

HML_t = Monthly return on the mimicking portfolio for book-to-market

MOM_t = Monthly return on the mimicking portfolio for momentum; and

DRF_t = Monthly return on the mimicking portfolio for difference of opinion.

The monthly returns of each of the 25 size and book-to-market portfolios are regressed on the model specified above. By regressing each portfolio's returns against the model, we can ascertain whether DRF is significant in explaining equity returns. Recall that the main objective of this paper is to test whether there is a relationship between future returns and DRF (constructed using DISP and maximum share turnover proxies). If a positive relationship exists, the factor premium for DRF should be positive and the DRF coefficient, d_p, for high (or low) difference of opinion portfolios will be significantly positive (or negative). If DRF is insignificant, this will imply that DRF does not have an effect on returns. If a negative relationship exists, the DRF factor premium will be negative and the DRF coefficient, d_p, for high (or low) difference of opinion portfolios will be significantly positive (or negative).

Based on Doukas et al.'s (2004) findings one could argue that large stocks and value stocks will load positively on the positive DRF while small stocks and growth stocks will load negatively on the positive DRF. Conversely, if Miller's model holds true, the DRF factor premium will be negative with small stocks and growth stocks loading positively on the negative DRF, and with large stocks and value stocks loading negatively on the negative DRF. In other words, regardless of whether the DRF is positive or negative, high-difference-of-opinion portfolios should have a positive coefficient d_p, and low-difference-of-opinion portfolios should have a negative coefficient.

2.2.2 GMM System Regressions

Besides running individual regressions on the 25 portfolios, we also employ the Generalized Method of Moments (GMM) system regression approach adopted by MacKinlay and Richardson (1991), Faff (2001), and Gharghori et al. (2006). The empirical modelling applied in this research is based on a Fama and French (1993) model enhanced with momentum and difference of opinion. Our model can be shown as:

$$E(R_p) – R_f = b_p[E(R_m) – R_f] + s_pE(SMB) + h_pE(HML) + m_pE(MOM) + d_pE(DRF) \qquad (2)$$

Recall that the empirical counterpart of this model is given by equation (1). In the context of our system-based estimation the null hypothesis is H_0: $a_p = 0$; p = 1, 2, …, N and the restricted version of equation (2) is thus given by:

$$r_{pt} = b_pRMF_t + s_pSMB_t + h_pHML_t + m_pMOM_t + d_pDRF_t + e_{pt} \qquad (3)$$

where $r_{pt} = R_{pt} – R_{ft}$ and $RMF_t = (R_{mt} - R_{ft})$.

We augment the system to allow a direct estimation of the premia for the five risk factors:

$$r_{pt} = b_pRMF_t + s_pSMB_t + h_pHML_t + m_pMOM_t + d_pDRF_t + e_{pt} \qquad (4)$$

$$RMF_t = \lambda_m + e_{bt} \qquad (5)$$

$$SMB_t = \lambda_{SMB} + e_{st} \qquad (6)$$

$$HML_t = \lambda_{HML} + e_{ht} \qquad (7)$$

$$MOM_t = \lambda_{MOM} + e_{mt} \qquad (8)$$

$$DRF_t = \lambda_{DRF} + e_{dt} \qquad (9)$$

Where p = 1, 2, ..., N.

Equations (5) to (9) impose a mean adjusted transformation on the independent variables in equation (4). Upon rearrangement, the null hypothesis is effectively a test of whether the intercept term a* is equal to a non-zero restriction:

$$H_0: a^* = b_p\lambda_m + s_p\lambda_{SMB} + h_p\lambda_{HML} + m_p\lambda_{MOM} + d_p\lambda_{DRF}$$

Since the intercept in equation (4) is restricted to 0, there exist 6N + 5 sample moment equations and 5N + 5 unknown parameters (i.e. $\phi = b_1, b_2, \ldots, b_N, s_1, s_2, \ldots, s_N, h_1, h_2, \ldots, h_N, m_1, m_2, \ldots, m_N, d_1, d_2, \ldots, d_N, \lambda_m, \lambda_{SMB}, \lambda_{HML}, \lambda_{MOM}, \lambda_{DRF}$). This means there are 6 sample moment conditions for each of N test equations, as follows: (a) the mean regression error term is zero and the regression error term is orthogonal to each regressor, namely, to (b) RMF_t; (c) SMB_t; (d) HML_t; (e) MOM_t; and (f) DRF_t.

Thus, the GMM statistic involves N over-identifying restrictions (distributed χ_N^2) and is given by:

$$GMM = (T - N - 1)^* g_T(\hat{\phi})' . S_T^{-1} . g_T(\hat{\phi}) \qquad (10)$$

Where $g_T(\hat{\phi}) = \frac{1}{T}\sum_{t=1}^{T} f_t(\hat{\phi})$, is the empirical moment condition vector; and GMM is (asymptotically) distributed as a chi-square statistic with N degrees of freedom.

There are several advantages in employing the system regressions approach over individual regressions. First, the system regression allows us to concurrently estimate the factor premiums of each explanatory variable. This allows testing for significance of the premia for the specified risk factors: H_0: $\lambda_m = 0$; H_0: $\lambda_{SMB} = 0$; H_0: $\lambda_{HML} = 0$; H_0: $\lambda_{MOM} = 0$; and H_0: $\lambda_{DRF} = 0$. According to Doukas et al. (2004), the factor premium of DRF should be positive and significant. However, Diether et al. (2002)

suggest that the factor premium of DRF should be negative and significant. This approach allows us to directly test which of the conflicting findings of Doukas et al. (2004) and Diether et al. (2002) is supported.

Second, the system regression allows us to perform regressions for all 25 portfolios simultaneously. The advantage here is that by observing the GMM statistic, it can be ascertained whether the specified regression model works on all 25 portfolios. Further, the GMM system regression also has its own specific advantages over a regular system regression. The main advantage is that it accounts for non-normality, heteroskedasticity and serial correlation in the residuals. If the data are either non-normal, heteroskedastic or autocorrelated, the assumptions of the OLS approach will be violated and the coefficients and standard errors will be incorrect. Thus, statistical inferences about the true population parameter's value will be misleading. We overcome this problem by using the GMM approach.

2.2.3 Modified Likelihood Ratio Test

We also employ the Modified Likelihood Ratio Test (MLRT) in order to test whether the DRF is useful in pricing assets. Specifically, the MLRT tests whether the coefficients on the DRF are jointly equal to zero. The MLRT test statistic used in our analysis is also adopted by Connor and Korajczyk (1988) and Faff (1992). The MLRT can be shown as:

$$MLRT = T * \left\{ \left[\frac{\det(\hat{\sum} r)}{\det(\hat{\sum} u)} \right] - 1 \right\} \qquad (11)$$

where

$\det(\hat{\sum} r)$ = the determinant of the maximum likelihood estimate of the error covariance matrix from the restricted system

$\det(\hat{\sum} u)$ = the determinant of the maximum likelihood estimate of the error covariance matrix from the unrestricted system

$T^* = (T – K – N) / N$; T = the number of time series observations

K = the number of factors, and

N = the number of equations in the multivariate regression system.

This statistic is identical to the statistic described in Gibbons, Ross, and Shanken (1986). Given the assumption of normality, the MLRT has an exact small-sample F distribution with (N, T – K – N) degrees of freedom. The null hypothesis for the case of zero joint mispricing is:

$$H_0: d_p = 0; p = 1, 2, \ldots, 25.$$

If the null hypothesis is not rejected, this implies that in the context of the entire system, the DRF has no ability to price the test portfolios. In the situation that the null hypothesis is rejected, the DRF is useful in pricing the test assets.

3. Empirical Findings

3.1 Descriptive Statistics and Correlations

Panel A of Table 1 reports the descriptive statistics obtained by our study. The time series means for the market factor (0.38% per month), SMB (3.33% per month), HML (0.87% per month), and MOM (0.87% per month) are all positive and significant. The mean for DRF (constructed using DISP) is negative and significant (-0.44% per month). The descriptive statistics indicate that SMB, HML, and MOM are most likely to be priced in equity returns, while the negative mean for DRF (constructed using DISP) indicates that stocks with high difference of opinion tend to underperform stocks with low difference of opinion. Our findings are consistent with Miller (1977) and Diether et al. (2002).

[Insert Table 1 about here]

Panel B of Table 1 reports the correlations. The correlation between the market factor and DRF (constructed using DISP) is positive and quite large (0.448). This suggests that the market factor and DRF are closely related and hence, some proportion of equity returns may be explained by both factors simultaneously. Doukas et al. (2004) claim that difference of opinion among investors can explain the value anomaly. If this is indeed true, we would expect to find that HML and DRF are highly positively correlated. However, we find the correlation between these two factors to be quite low (0.123). Hence, the combined evidence in Panels A and B suggest that it is unlikely that the value anomaly is explained by difference of opinion. Besides the high correlation between the market factor and DRF, the other independent variables have weak correlations among them.

3.2 DRF (DISP) Augmented Fama-French and Carhart Regressions

Table 2 reports the results of the 25 individual regressions of the DRF (using DISP) augmented Fama-French model. The factor loading on DRF (constructed using DISP), d_p, is significant for only 3 out of 25 portfolios. The poor ability of the DRF to explain the variability in equity returns is also highlighted by the average adjusted R^2 of the DRF augmented Fama-French model. The average adjusted R^2 of 0.555 is only marginally higher than the Fama-French model's average adjusted R^2 of 0.553, implying that the DRF explains very little of the cross-sectional variation in equity returns.

[Insert Table 2 about here]

Table 3 reports the results of the individual DRF augmented Carhart regressions. Our findings show that the factor loading for momentum, (m_p), is significant for only 4 out of 25 portfolios. We also find that the factor loading for DRF

(d_p) is significant for only 3 out of 25 portfolios. Similar to the DRF augmented Fama-French model, the introduction of the DRF in the Carhart model fails to improve the model's explanatory power. The average adjusted R^2 for the Carhart and the DRF augmented Carhart models are almost identical.[9]

[Insert Table 3 about here]

3.3 System Regressions

Table 4 reports the results of the GMM system estimation and the tests of the Fama-French, Carhart, DRF augmented Fama-French, and DRF augmented Carhart models. The first system regression reported is for the Fama-French model. Our results show that the GMM statistic is insignificant, which supports the overall favourability of the Fama-French model. We find that the market premium (λ_m) is positive and statistically significant (t-statistic of 2.44). Similarly, the factor premiums for SMB and HML are also positive and significant (t-statistic of 8.15 for λ_{SMB} and 2.64 for λ_{HML}). This shows that the Fama-French factors represent risk factors that are priced in equity returns and not explained by the market factor.

[Insert Table 4 about here]

The second system regression reported in Table 4 is for the Carhart model. An interesting finding here is that the inclusion of the momentum factor (MOM) results in the market premium (λ_m) becoming insignificant (t-statistic of 1.90). However, the premiums for SMB and HML are positive and significant (t-statistic of 7.31 for λ_{SMB} and 3.66 for λ_{HML}) even after the inclusion of the MOM factor. The

[9] The results of the individual regressions using the Fama-French and Carhart models have not been reported but are available from the authors upon request.

premium for the momentum factor (λ_{MOM}) is positive and statistically significant (t-statistic of 3.47) indicating that the factor is priced and not explained completely by SMB, HML or the market factor.

Additionally, the GMM statistic is insignificant (t-statistic of 0.204) for the Carhart model. Similar to the Fama-French model, the insignificant GMM statistic implies that the GMM test supports the overall favourability of the Carhart model. Even though the factor premium of momentum is significant in the system regression, we down-weight the results of the system regression due to the insignificant findings in the individual regressions.

The third system regression in Table 4 is for the DRF (DISP) augmented Fama-French model. Similar to the system regression results of the Fama-French model, the factor premiums for the market (λ_m), SMB (λ_{SMB}), and HML (λ_{HML}) are all significantly positive. The factor premium for the DRF (λ_{DRF}) is significantly negative (t-statistic of -2.93). This implies that high-difference-of-opinion stocks underperform low-difference-of-opinion stocks and that difference of opinion is not a risk factor.

This finding is inconsistent with difference of opinion being a risk factor (Doukas, 2004) and instead provides support for Miller's (1977) model. The inclusion of the DRF also reduces the factor premiums for both the market (λ_m) and SMB (λ_{SMB}) but increases the factor premium for HML (λ_{HML}). This increase provides evidence to rebut the argument of Doukas et al. (2004) that difference of opinion explains the value anomaly. If this were so, we would expect to find the HML factor premium to be insignificant when the model is augmented with DRF. Given that it actually increases in the presence of DRF, it is unlikely that DRF or difference of opinion explains the value anomaly. Again, the GMM statistic is insignificant (t-statistic 0.205); thus, the GMM statistic supports the overall favourability of the DRF augmented Fama-French model.

The fourth system regression reported in Table 4 is for the DRF augmented Carhart model. We observe that the market factor premium becomes insignificant (t-statistic 1.86) at the 5% level. The factor premiums for SMB, HML, and MOM remain positively significant. Again, the premium for the DRF is negatively significant. Hence, this implies that the DRF is not a priced risk factor in equity returns. Similar to the results for the third regression (DRF augmented Fama-French model), the positively significant HML factor again shows that difference of opinion does not explain the value anomaly and that HML is the superior proxy for the value anomaly. Finally, the GMM statistic is insignificant and hence the DRF augmented Carhart model cannot be rejected.

Overall, the system regressions show that the models cannot be rejected. The system regression approach also shows that the estimated market factor premium (λ_m) is positive and significant for the Fama-French and the DRF augmented Fama-French models. However, the market factor premium ceases to be significant once the MOM factor is added. In contrast, the SMB and HML factor premiums remain positively significant across all models. For the Carhart models, the MOM factor premium is positively significant, implying that this factor is priced. The last column in Table 4 reports the results from the Modified Likelihood Ratio Test (MLRT) for the DRF augmented Fama-French model and the DRF augmented Carhart model. The p-values for both models show that the null hypothesis, H_0: d_p = 0, cannot be rejected. This implies that the coefficients on the DRF are jointly equal to zero and that the DRF is unlikely to be useful in the pricing of assets.

The system regressions reported in Table 5 are for the DRF augmented Fama-French and Carhart models, where DRF is constructed using maximum share turnover. The results observed for these two regressions are very similar to the system regression results for the previous DRF augmented Fama-French and Carhart models where DRF is created using DISP (Table 4). Specifically, the DRF factor premium is significant and negative for both the system regressions reported.

Thus, the combined evidence from Tables 4 and 5 suggests that DRF is not a priced risk factor and is negatively related to equity returns. The last column in Table 5 reports the results from the MLRT. In contrast to the results in Table 4, the null hypothesis, H_0: $d_p = 0$, is rejected for both the DRF augmented Fama-French and Carhart models. This implies that the coefficients on DRF are not jointly equal to zero and that the DRF constructed using maximum turnover is somewhat useful in pricing the test assets[10].

[Insert Table 5 about here]

[10] The results of individual regressions that employ maximum share turnover as a proxy for difference of opinion have not been reported but are available from the authors upon request.

4. Conclusions

Previous empirical research conducted in the US on the relationship between difference of opinion and stock returns have yielded mixed results. This paper provides out of sample evidence on the relationship between difference of opinion and stock returns. It makes several contributions.

First, the study uses two proxies for measuring difference of opinion among investors. Second, it adopts the GMM system regression approach to test the relationship between difference of opinion and stock returns. The GMM system approach provides a stronger test than the use of individual regressions, as all the 25 portfolios can be run simultaneously. The GMM system also enables us to examine the individual factor premiums of the independent variables. Third, this study examines whether difference of opinion can be used to explain the value anomaly.

Overall, the results document a significant negative relationship between difference of opinion (using both the dispersion in analysts' forecasts proxy and the maximum share turnover proxy) and stock returns. This result provides strong support for Miller's (1977) model and is consistent with the findings of Diether et al. (2002). Thus, we are unable to support the risk-based argument advanced by Doukas et al. (2004). Our findings also reject the claim that difference of opinion could explain the value anomaly. In short, we do not find DRF to be useful in explaining the variation in average stock returns. Despite using maximum share turnover as an alternative proxy, our study suffers from sample bias in that the proxy is calculated for stocks that have been trading for at least 245 days. It is worth noting that stocks that trade for at least 245 days are large stocks. As we reduce the number of trading days for each stock to be included in our study, the results become insignificant. We suggest that future research should focus on deriving a proxy for difference of opinion which does not suffer from the sample bias problem.

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Table 1

Basic Descriptive Statistics and Correlations

This table reports basic descriptive statistics and correlations for the five factors used in this analysis for the period January 1990 to December 2005. The DRF is constructed using the dispersion in analysts' earnings forecasts (DISP). RMF is the monthly excess return of the value-weighted market portfolio. SMB represents the monthly return on the size-mimicking portfolio. HML represents the monthly return on the book-to-market-mimicking portfolio. MOM represents the monthly return on the momentum-mimicking portfolio. DRF represents the monthly return on the difference of opinion mimicking portfolio.

Panel A: Descriptive Statistics

	RMF	SMB	HML	MOM	DRF
Mean	0.0038	0.0333	0.0087	0.0087	-0.0044
Mean Std Error	0.0024	0.0049	0.0035	0.0038	0.0015
t-statistic	1.5659	6.7568	2.5260	2.2766	-2.8270
Median	0.0080	0.0214	0.0076	0.0086	-0.0036
Maximum	0.0731	0.3645	0.2989	0.1781	0.0510
Minimum	-0.1059	-0.2029	-0.1777	-0.3352	-0.0974
Std. Dev.	0.0334	0.0684	0.0479	0.0532	0.0215
Skewness	-0.5851	1.1101	1.4387	-1.3229	-0.6133
Kurtosis	3.3118	6.4093	13.9789	11.6622	4.5830

Panel B: Correlations

	RMF	SMB	HML	MOM	DRF
RMF	1.000				
SMB	0.083	1.000			
HML	0.004	-0.202	1.000		
MOM	-0.104	-0.029	-0.178	1.000	
DRF	0.448	0.054	0.123	-0.204	1.000

Table 2

Individual Regressions of a Difference of Opinion (DISP) Augmented Fama-French Model on 25 Size- and Book-to-Market-Sorted Portfolios

This table reports the results of individual regressions of a difference of opinion (DISP) augmented Fama-French model on 25 size- and BM-sorted portfolios for the period January 1990 to December 2005. The SMB and HML portfolios are created following the methodology employed by Fama and French (1993). The DRF is constructed as follows: First, the DISP measure is obtained for all stocks which have at least two analysts following them. The stocks are further sorted into three equally-weighted DISP portfolios (Low, Medium, and High). Stocks are ranked in December of year t – 1 and placed into the three portfolios (based on DISP rankings) from January to December of year t. DRF is the difference, each month, between the equally-weighted returns on the high-DISP portfolio and the equally-weighted returns on the low-DISP portfolio. Monthly returns are computed for these portfolios for the following 12 months and this process is repeated annually. b_p represents the factor loading on the monthly excess return of the value-weighted market portfolio. s_p is the factor loading for the monthly return on the size-mimicking portfolio. h_p is the factor loading for the monthly return on the book-to-market-mimicking portfolio. d_p is the factor loading for the monthly return on the difference of opinion mimicking portfolio.

Size	BM	a_p	b_p	s_p	h_p	d_p	Adj R^2
1	1	0.0341	1.3500	1.1520	-0.4700	0.4053	0.460
		(3.95)	(5.21)	(9.60)	(-3.19)	(1.01)	
1	2	0.0206	0.9695	1.4539	-0.1807	0.2050	0.552
		(2.58)	(3.68)	(11.14)	(-0.76)	(0.61)	
1	3	0.0391	0.8823	1.2756	-0.4250	0.4668	0.467
		(4.53)	(3.64)	(11.11)	(-1.91)	(1.34)	
1	4	0.0154	1.2618	1.2367	0.1284	0.1020	0.628
		(2.77)	(7.11)	(9.81)	(0.60)	(0.30)	
1	5	0.0146	0.8697	1.6325	1.4711	0.2540	0.583
		(1.24)	(3.12)	(5.77)	(2.07)	(0.52)	
2	1	0.0054	1.1038	0.9587	-0.7804	0.0939	0.594
		(1.03)	(5.03)	(8.82)	(-3.86)	(0.28)	
2	2	0.0033	0.8237	1.0562	-0.1319	0.2981	0.596
		(0.64)	(5.25)	(9.23)	(-0.74)	(1.13)	
2	3	0.0049	1.3416	1.1175	0.2408	-0.4051	0.491
		(0.72)	(5.65)	(5.30)	(1.16)	(-0.83)	
2	4	0.0033	0.8414	0.8971	0.0542	0.0554	0.534
		(0.81)	(5.40)	(7.43)	(0.33)	(0.23)	
2	5	0.0088	0.6620	0.7101	0.1762	0.2873	0.591
		(2.84)	(5.80)	(7.72)	(1.48)	(1.60)	
3	1	0.0043	1.0891	0.6875	-0.3811	0.1916	0.600
		(0.93)	(8.22)	(10.69)	(-3.24)	(1.11)	
3	2	-0.0002	0.8934	0.6131	-0.0473	0.1133	0.550
		(-0.05)	(7.14)	(6.63)	(-0.38)	(0.63)	
3	3	0.0038	0.7757	0.4322	-0.0085	0.3647	0.599
		(1.20)	(8.38)	(10.59)	(-0.12)	(2.46)	
3	4	0.0090	0.6729	0.3220	0.1198	0.4707	0.499
		(2.99)	(7.13)	(5.21)	(1.31)	(3.13)	
3	5	0.0057	0.9535	0.5711	0.5813	-0.1034	0.274
		(0.73)	(5.10)	(3.02)	(1.38)	(-0.30)	
4	1	0.0016	0.8673	0.3463	-0.1088	0.2185	0.568
		(0.47)	(10.52)	(6.68)	(-2.00)	(1.86)	
4	2	0.0049	0.8925	0.2489	0.0515	0.0442	0.592
		(2.07)	(11.18)	(5.79)	(0.95)	(0.37)	
4	3	0.0036	0.7739	0.2246	0.0053	0.1372	0.651

Size	BM	a_p	b_p	s_p	h_p	d_p	Adj R^2
		(1.83)	(13.51)	(6.80)	(0.10)	(1.52)	
4	4	0.0103	0.6695	0.0967	0.0340	0.1848	0.483
		(4.44)	(10.77)	(2.42)	(0.56)	(1.82)	
4	5	0.0086	0.7808	0.0992	0.2511	0.0579	0.260
		(2.26)	(5.15)	(2.00)	(2.04)	(0.30)	
5	1	0.0024	0.9421	-0.0013	-0.1052	-0.0941	0.698
		(1.30	(16.48)	(-0.05)	(-2.85)	(-1.15)	
5	2	0.0050	1.0255	-0.0331	-0.0530	0.1093	0.856
		(4.18)	(27.69)	(-1.49)	(-2.11)	(2.04)	
5	3	0.0073	1.0059	-0.0677	0.0802	-0.0471	0.758
		(4.43)	(25.08)	(-2.71)	(2.62)	(-0.68)	
5	4	0.0042	1.1430	-0.0531	0.2617	-0.0525	0.648
		(1.81	(15.17)	(-1.49)	(3.51)	(-0.30)	
5	5	0.0070	0.8437	0.0974	0.4088	0.2863	0.356
		(1.77)	(6.03)	(1.96)	(4.47)	(1.31)	
Average							0.555

Table 3

Individual Regressions of a Difference of Opinion (DISP) Augmented Carhart Model on 25 Size- and Book-to-Market-Sorted Portfolios

This table reports the results of individual regressions of a difference of opinion (DISP) augmented Carhart model on 25 size- and BM-sorted portfolios for the period January 1990 to December 2005. SMB and HML are created following the methodology employed by Fama and French (1993), and the MOM factor is created following Carhart (1997). The DRF is constructed as follows: First, the DISP measure is obtained for all stocks which have at least two analysts following the stock. The stocks are further sorted into three equally-weighted DISP portfolios (Low, Medium, and High). Stocks are ranked in December of year t – 1 and placed into the three portfolios (based on DISP rankings) from January to December of year t. DRF is the difference, each month, between the equally-weighted returns on the high-DISP portfolio and the equally-weighted returns on the low-DISP portfolio. Monthly returns are computed for these portfolios for the following 12 months and this process is repeated annually. b_p represents the factor loading on the monthly excess return of the value-weighted market portfolio. s_p is the factor loading for the monthly return on the size-mimicking portfolio. h_p is the factor loading for the monthly return on the book-to-market-mimicking portfolio. m_p is the factor loading for the monthly return on the momentum-mimicking portfolio. d_p is the factor loading for the monthly return on the difference of opinion mimicking portfolio.

Size	BM	a_p	b_p	s_p	h_p	m_p	d_p	Adj R^2
1	1	0.0321	1.3572	1.1602	-0.4325	0.2008	0.4901	0.462
		(3.67)	(5.24)	(10.28)	(-2.86)	(1.15)	(1.180	
1	2	0.0191	0.9750	1.4601	-0.1524	0.1517	0.2690	0.552
		(2.33)	(3.69)	(11.47)	(-0.67)	(1.23)	(0.80)	
1	3	0.0400	0.8792	1.2721	-0.4411	-0.0861	0.4305	0.465
		(4.62)	(3.62)	(11.35)	(-1.97)	(-0.53)	(1.20)	
1	4	0.0125	1.2721	1.2485	0.1824	0.2892	0.2241	0.642
		(2.35)	(7.41)	(10.81)	(0.95)	(2.49)	(0.69)	
1	5	0.0177	0.8585	1.6197	1.4125	-0.3144	0.1213	0.591
		(1.45)	(3.12)	(5.85)	(2.06)	(-1.50)	(0.26)	
2	1	0.0070	1.0981	0.9522	-0.8105	-0.1610	0.0259	0.597
		(1.28)	(5.01)	(8.83)	(-3.98)	(-1.57)	(0.08)	
2	2	0.0027	0.8257	1.0585	-0.1214	0.0565	0.3220	0.594
		(0.52)	(5.30)	(9.39)	(-0.70)	(0.65)	(1.22)	
2	3	0.0059	1.3379	1.1132	0.2214	-0.1043	-0.4491	0.490
		(0.90)	(5.65)	(5.36)	(1.09)	(-1.08)	(-0.90)	
2	4	0.0025	0.8444	0.9005	0.0698	0.0835	0.0906	0.534
		(0.57)	(5.33)	(7.43)	(0.41)	(1.06)	(0.37)	
2	5	0.0091	0.6611	0.7090	0.1710	-0.0275	0.2757	0.589
		(2.87)	(5.78)	(7.60)	(1.48)	(-0.37)	(1.47)	
3	1	0.0039	1.0903	0.6889	-0.3748	0.0337	0.2058	0.598
		(0.83)	(8.22)	(10.58)	(-3.08)	(0.45)	(1.14)	
3	2	-0.0006	0.8946	0.6145	-0.0408	0.0350	0.1281	0.548
		(-0.13)	(7.05)	(6.65)	(-0.34)	(0.29)	(0.68)	
3	3	0.0043	0.7739	0.4302	-0.0176	-0.0491	0.3439	0.599
		(1.34)	(8.50)	(10.96)	(-0.24)	(-0.93)	(2.34)	
3	4	0.0093	0.6720	0.3210	0.1151	-0.0247	0.4602	0.497
		(3.13)	(7.14)	(5.19)	(1.25)	(-0.50)	(2.92)	
3	5	0.0046	0.9575	0.5756	0.6020	0.1109	-0.0566	0.273
		(0.53)	(5.08)	(3.01)	(1.42)	(0.69)	(-0.18)	
4	1	0.0007	0.8705	0.3499	-0.0922	0.0888	0.2559	0.573
		(0.20)	(10.49)	(7.03)	(-1.67)	(1.11)	(2.16)	
4	2	0.0056	0.8901	0.2462	0.0391	-0.0665	0.0161	0.595

Size	BM	a_p	b_p	s_p	h_p	m_p	d_p	Adj R^2
		(2.28)	(11.33)	(5.77)	(0.73)	(-1.61)	(0.14)	
4	3	0.0044	0.7709	0.2211	-0.0105	-0.0844	0.1016	0.661
		(2.26)	(13.44)	(7.00)	(-0.21)	(-2.39)	(1.05)	
4	4	0.0114	0.6658	0.0925	0.0149	-0.1024	0.1416	0.501
		(5.12)	(11.32)	(2.58)	(0.26)	(-2.79)	(1.40)	
4	5	0.0092	0.7785	0.0966	0.2393	-0.0634	0.0311	0.259
		(2.27)	(5.17)	(1.88)	(2.00)	(-0.92)	(0.16)	
5	1	0.0016	0.9450	0.0020	-0.0897	0.0828	-0.0592	0.710
		(0.93)	(17.70)	(0.09)	(-2.82)	(2.82)	(-0.75)	
5	2	0.0051	1.0250	-0.0337	-0.0558	-0.0152	0.1029	0.856
		(4.30)	(27.81)	(-1.52)	(-2.22)	(-0.69)	(1.92)	
5	3	0.0078	1.0041	-0.0697	0.0709	-0.0498	-0.0682	0.761
		(4.62)	(24.54)	(-2.98)	(2.19)	(-1.38)	(-0.98)	
5	4	0.0044	1.1425	-0.0537	0.2590	-0.0144	-0.0586	0.646
		(1.76)	(15.10)	(-1.50)	(3.37)	(-0.35)	(-0.33)	
5	5	0.0076	0.8417	0.0952	0.3986	-0.0546	0.2632	0.354
		(1.84)	(6.02)	(1.85)	(4.23)	(-1.14)	(1.21)	
Average								0.558

Table 4

Generalized Method of Moments (GMM) System Tests of the Asset Pricing Models Specified (Dispersion in analysts' earnings forecasts proxy)

The test of the difference of opinion (DISP) augmented Carhart model is based on the following system:

$$r_{pt} = b_p RMF_t + s_p SMB_t + h_p HML_t + m_p MOM_t + d_p DRF_t + \varepsilon_{pt} \qquad [p = 1, 2, \ldots, N] \qquad (4)$$

$$RMF_t = \lambda_m + \varepsilon_{bt} \qquad (5)$$

$$SMB_t = \lambda_{SMB} + \varepsilon_{st} \qquad (6)$$

$$HML_t = \lambda_{HML} + \varepsilon_{ht} \qquad (7)$$

$$MOM_t = \lambda_{MOM} + \varepsilon_{mt} \qquad (8)$$

$$DRF_t = \lambda_{DRF} + \varepsilon_{dt} \qquad (9)$$

The generalized method of moments (GMM) test statistic, testing that the asset pricing models hold, is distributed as a chi-square with N degrees of freedom. The statistic has had the small sample adjustment applied following MacKinlay and Richardson (1991). The associated p-value is contained in parentheses below the GMM statistic. The associated t-statistic for the factor premiums is contained in parentheses below the coefficient estimates. The MLRT, testing that the 25 coefficients on DRF are jointly equal to zero, has an F distribution with (25, 163) degrees of freedom for the DRF augmented Fama French model and (25, 162) degrees of freedom for the DRF augmented Carhart model. The associated p-value is reported below the MLRT statistic in parentheses. The test period is from January 1990 to December 2005.

	GMM	λ_m	λ_{SMB}	λ_{HML}	λ_{MOM}	λ_{DRF}	MLRT, H_0: $d_p = 0$
FF	33.45	0.0046	0.0372	0.0061			
	(0.202)	(2.44)	(8.15)	(2.64)			
Carhart	33.89	0.0035	0.0337	0.0079	0.0113		
	(0.204)	(1.90)	(7.31)	(3.66)	(3.47)		
FF DRF (DISP)	33.96	0.0040	0.0356	0.0067		-0.0050	1.127
	(0.205)	(2.23)	(7.62)	(2.81)		(-2.93)	(0.32)
Carhart DRF (DISP)	34.27	0.0033	0.0328	0.0078	0.0120	-0.0053	1.114
	(0.206)	(1.86)	(6.92)	(3.43)	(3.60)	(-3.23)	(0.33)

Table 5

Generalized Method of Moments (GMM) System Tests of the Asset Pricing Models Specified (Maximum share turnover proxy)

The test of the difference of opinion (Maximum share turnover) augmented Carhart model is based on the following system:

$$r_{pt} = b_p RMF_t + s_p SMB_t + h_p HML_t + m_p MOM_t + d_p DRF_t + \varepsilon_{pt} \qquad [p = 1, 2, \ldots, N] \qquad (4)$$

$$RMF_t = \lambda_m + \varepsilon_{bt} \qquad (5)$$

$$SMB_t = \lambda_{SMB} + \varepsilon_{st} \qquad (6)$$

$$HML_t = \lambda_{HML} + \varepsilon_{ht} \qquad (7)$$

$$MOM_t = \lambda_{MOM} + \varepsilon_{mt} \qquad (8)$$

$$DRF_t = \lambda_{DRF} + \varepsilon_{dt} \qquad (9)$$

The DRF using maximum share turnover as a proxy for difference of opinion proxy is constructed as follows: First, maximum share turnover is calculated for all stocks in December of year t – 1. Maximum share turnover is defined as the average daily adjusted share turnover of the highest 5-day period during the past year minus the average daily adjusted share turnover during the rest of the year excluding a 5-day window before and a 5-day window after the 5-day maximum. Stocks that have traded for less than 245 days in the past year are removed from the sample. Once maximum share turnover is determined, stocks are sorted into three equally-weighted portfolios (Low, Medium, and High) from January to December of year t. The returns are recorded each month for each of these three portfolios. DRF is the difference each month between the equally-weighted returns on the high maximum share turnover portfolio and the equally-weighted returns on the low maximum share turnover portfolio. The portfolios are rebalanced annually.

The generalized method of moments (GMM) test statistic, testing that the asset pricing models hold, is distributed as a chi-square with N degrees of freedom. The statistic has had the small sample adjustment applied following MacKinlay and Richardson (1991). The associated p-value is contained in parentheses below the GMM statistic. The associated t-statistic for the factor premiums is contained in parentheses below the coefficient estimates. The MLRT, testing that the 25 coefficients on DRF are jointly equal to zero, has an F distribution with (25, 150) degrees of freedom for the DRF augmented Fama French model and (25, 149) degrees of freedom for the DRF augmented Carhart model. The associated p-value is reported below the MLRT statistic in parentheses. The test period is from January 1990 to December 2004.

	GMM	λ_m	λ_{SMB}	λ_{HML}	λ_{MOM}	λ_{DRF}	MLRT, H_0: $d_p = 0$
FF DRF (Maximum Share Turnover)	31.52	0.0030	0.0319	0.0083		-0.0124	4.399
	(0.205)	(1.60)	(6.45)	(3.56)		(-3.08)	(0.00)
Carhart DRF (Maximum Share Turnover)	32.01	0.0023	0.0304	0.0083	0.0209	-0.0137	4.622
	(0.208)	(1.27)	(6.30)	(3.91)	(5.20)	(-3.21)	(0.00)