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Short Sale Constraints, The Suppression of Negative Opinions in Equity Markets, and Valuation

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Abstract

With seventeen years having passed since Diether, Malloy, and Scherbina (2002) demonstrated that stocks with greater dispersion in analyst forecasts have lower returns going forward, this paper aims to test this anomaly on new data. Contrary to the trend shown previously, the anomaly has not been disappearing, and there is no significant difference in excess returns from a self-financing long-short strategy based on the anomaly between the 1980s and 2010s. This is further evidence supporting the hypothesis that short sale constraints suppress negative views on valuations. The results imply neither disagreement nor short sale constraints have declined significantly up to now. The debate surrounding earnings guidance as well as that around short sale constraints should strongly consider these results to ensure that markets are accurately valuing stocks.

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Introduction

A fundamental debate, if not the fundamental debate, in finance is that surrounding the efficient market hypothesis. If markets incorporate all available information into prices, then there should be no systematic variation in returns once risk has been accounted for. Therefore, at the centre of the efficient market debate are anomalies that are seemingly mispricings in the market, unexplained by risk.

While many of these anomalies have been identified, there are accusations of "p hacking" (Hou et al, 2018, p. 5), using statistical techniques until significance is found. However, there are some of more interest. In particular, there is the anomaly inspired by Miller in 1977 predicting that a combination of short sale constraints and disagreement over an assets fundamental value could lead to a systematic overpricing of applicable assets. This was just a theory, and unusually for anomalies, the theory came well before empirical tests of it.

In 2002, Diether, Malloy, and Scherbina looked for the anomaly predicted by Miller and found its existence in the data. Despite this, they also found that its magnitude and significance was declining through time, which they suggested could be as a result of both falling disagreement and weakening short sale constraints (Diether et al, 2002, pp. 2132 – 2133).

Now there is 18 years of additional data on which to test the anomaly proposed by Miller, and this is the aim of this paper. Interestingly, in detailed results presented here, the anomaly has not disappeared like others. In fact, a strategy long the 20% of stocks with the lowest level of dispersion and short the 20% of stocks with the highest level in any given month has averaged a highly significant excess return of 0.51% per month from 1983 - 2018, when controlling for common risk factors and anomalies[1]. Within this there was a slight weakening of the anomaly from 1992 – 2009, followed by a return in 2010 – 2018 to the same magnitude of the 1983 – 1991 period.

These results imply two alternatives. Either Miller was correct in his hypothesis and therefore disagreement and short sale constraints have remained fairly constant. Alternatively, he did not accurately capture the behaviour of financial markets and there is some other theory that explains the anomaly captured in this paper. Until a credible theory, supported by data, is put forward and tested the evidence is supportive of the Miller hypothesis.

[1] This is for the time period from January 1983 to June 2018 when controlling for the following factors: Market Risk Premium, High Minus Low, Small Minus Big, Betting Against Beta

Some important implications arise from this research and the Miller hypothesis. Firstly, policymakers should think carefully when implementing impediments to short selling if they want markets to function well, accurately value assets and, therefore, correctly allocate capital. Secondly, this potential for overvaluation should be incorporated into the debate on earnings guidance, as increasing guidance could reduce disagreement and therefore improve valuation. Finally, whichever side of the debate you are on, the fact this paper replicates the results of Diether, Malloy, and Scherbina (2002) in the same time period gives comfort that revisions to the IBES database do not seem to have a material impact on results generated from its data.

Literature Review

In 1977 Edward Miller published his seminal paper *Risk, Uncertainty, and Divergence of Opinion*, which outlined an intuitive model of asset pricing when there is disagreement amongst investors on the fundamental value of the asset, something many early rational expectations models left little room for. Among the key predictions of this paper is one that has stimulated much research in the years following the publication of the Miller paper. It is that in the presence of disagreement over the fundamental asset value, short sale constraints will prevent the so-called pessimists from communicating their pessimism on the value and so the asset will become overvalued relative to the average opinion of the market. In particular, the greater the level of disagreement over the true asset value, the greater the overvaluation, as the average optimist is more optimistic, and the average pessimist is more pessimistic.

The predictions of Miller have been countered, in particular by developments in the rational expectations framework, including from Diamond and Verrechia (1987) and Jarrow (1980). Diamond and Verrechia contains a model in which a rational market maker knows who informed and uninformed investors are and so adjusts prices to account for dispersion in opinion. Cornelli and Yilmaz (2015) relaxes this key assumption and instead market makers have prior beliefs over the number of informed and uninformed investors. These beliefs could either underestimate or overestimate the mix of investors so prices could be biased in both directions. A more recent development in the literature comes from Nezafet, Wang, and Schroder (2017), which relaxes the exogenous information gathering by investors implicit in the above models. Instead informed agents undertake an information gathering process, thus it is endogenous. Short selling constraints reduce the marginal value of information gathering, so there is less of it, and the price is less informative. This increases the risk of the asset, reducing demand for it from long investors and reducing its price. This is a secondary effect of short sale constraints, alongside the one proposed by Miller, and so short selling constraints can result in both over and under valuation. In particular, whenever investor risk aversion is high, for example in an economic downturn, then the endogenous information gathering effect is likely to be greater than the Miller effect, leading to a fall in asset prices. This paper acts as a theoretical justification for some of the earlier empirical findings that the 2008 short sale ban did not increase asset prices. While these theoretical models were being developed, empirical tests of the Miller hypothesis were being undertaken.

One of the leading tests of the Miller hypothesis is the Diether, Malloy, and Scherbina[2] paper (2002), which will form the backbone of this paper. Whilst its methodology will be discussed further later, DMS finds that stocks with a high level of dispersion in analyst forecasts have lower returns going forward than those with a low level of dispersion, supporting the Miller hypothesis. In particular, a portfolio which is long the quintile of lowest dispersion stocks and short the quintile of the highest dispersion stocks returned on average 9.48% annually, a return that is highly significant. Other papers following slightly different methodologies but returning similar results in support of Miller include Chen, Hong and Stein (2002), Boehme, Danielsen and Sorescu (2006), and Ofek and Richardson (2003).

Not only is there empirical evidence that the dispersion hypothesis explains the cross sections of stock returns, but there is also evidence suggesting that it helps to explain aggregate stock market returns. Park (2005) shows that dispersion of analyst forecasts for the aggregate S&P 500 earnings per share can predict lower aggregate stocks returns going forward. Yu (2011) builds a bottom up measure of aggregate market dispersion in beliefs by aggregating analyst disagreement on an individual stock level. Again, this demonstrates the relationship predicted by Miller (1977), that higher dispersion of beliefs will lead to lower future returns.

Alongside these direct tests of Miller, many papers have documented the effect of short sale constraints alone on valuation, and many find that short sale constraints lead to a consistent overpricing of assets, with lower abnormal returns going forward. These include Figlewski and Webb (1993), Ackert and Athanassalos (2005), and Jones and Lamont (2002).

The 2008 financial crisis resulted in short sale bans on some stocks around the world, with the aim of supporting prices, and these bans presented an opportunity for an experimental test of the Miller hypothesis. A series of papers have looked into the impact of these bans including Beber and Pagano (2013), Autore et al. (2011), and Boehmer et al. (2013). Autore et al. (2011) finds some evidence in support of Miller, but the other papers do not. Boehmer et al. (2013) finds that once controlling for bail outs prices were not supported and Beber and Pagano (2013) finds that prices were only supported for US financial stocks. Overall there is a degree of weakness in interpreting these results however, as the period in question was only a very limited time period, in which there were exceptional events.

However, the empirical evidence for Miller is not entirely agreed upon, with a counter argument coming from Avramov et al (2009). That paper finds evidence that the excess returns that appear to be generated by the dispersion hypothesis are actually explained by financial

[2] The Diether, Malloy, and Scherbina (2002) paper will from now on be referred to as DMS

distress. In particular, they find that the profits from trading on dispersion are concentrated amongst firms with the lowest credit ratings, as well as only during periods when credit conditions for the company are worsening.

Though the literature has been well developed, there is still plenty of room for further research in the area. In particular, focusing on DMS, the data analysing the anomaly only goes up to 2000, and there is now nearly 18 years of additional data on which the Miller hypothesis can be tested. This can test whether the declining magnitude and significance of the anomaly through time, as shown in DMS (2002, p. 2133) has continued. It is possible that arbitrageurs have begun to take advantage of the anomaly, thus leading to its disappearance. Chordia, Subrahmayam and Tong (2014) document the widespread disappearance of many anomalies that were previously found and attribute the decline to a variety of factors, including the increasing assets under management of hedge funds and higher short interest. Other papers documenting these disappearances include McLean and Pontiff (2016), who attribute the disappearance to research drawing attention to anomalies, which investors then exploit. Harvey, Liu, and Zhu (2016) argue that anomalies disappear when higher statistical thresholds are used, including a t-statistic of at least three. Another seminal paper, that of Schleifer and Vishny (1997) can provide an interesting angle into the disappearance of anomalies. They argue that there are informed arbitrageurs who are delegated funds by naïve investors. Arbitrage may result in short run losses leading naïve investors to remove funds. It may be reasonable to hypothesise that naïve investors have learnt over time, from examples such as Tiger Management (Brunnermeier and Nagel, 2004), that investing in arbitrageurs requires a certain level of trust and long-term focus. Therefore, the limits to arbitrage would reduce over time, in turn reducing the abnormal returns from anomalies. This presents a clear opportunity to further test the Miller hypothesis for the period since 2000, which this paper will endeavour to do.

Hypotheses to test

With the state of the current literature as documented above a couple of hypotheses will form the basis of this research paper

Hypothesis 1: The returns to the anomaly documented in DMS have declined over time

Hypothesis 2: The returns have declined more for large stocks as these have experienced falling short sale constraints and contain greater value, so it is more profitable to trade on them

Methodology

As touched upon in the literature review, this paper will broadly replicate the methodology of DMS, whilst diverging somewhat in the analysis of a long-short portfolio based on Miller's disagreement hypothesis.

Proxying Dispersion of Beliefs

The first challenge is to develop a proxy for dispersion of beliefs over a stocks fundamental value, a key pillar of the Miller hypothesis. For this, analyst forecasts of the current fiscal year-end earnings per share will be used, as in DMS. Analyst forecasts are widely used in the literature, with Boehme et al. (2006, pp. 463 - 464) also using current fiscal year-end earnings per share and Yu (2011, p. 164) using forecasts of the long-term growth rate of earnings per share. Though the Yu paper lists some benefits to using the long-term growth rate this paper will use current fiscal year-end earnings per share, in order to ensure comparability with DMS.

Dispersion is measured as the standard deviation of analyst forecasts divided by the mean forecast, which ensures it is scaled for direct comparability across firms. One issue noted in DMS (2002, p. 2118) is that this by definition requires at least two analyst forecasts in order for there to be a standard deviation, which significantly reduces the sample size available for analysis. More recently, Boehme et al (2006, pp. 468 – 469) attempts to increase the sample size by developing a unitary measure of dispersion using other proxies for dispersion, such as turnover. Though this greater sample size may be of some benefit to add credibility to results, La Porta (1996, p. 1719) notes that it has been shown that the performance of stocks in the IBES sample closely follows that of those in all of CRSP, so including more stocks would not significantly change results. Alongside this, and as with using fiscal year-end earnings per share, the methodology of DMS will be followed to ensure direct comparability of results

Creating and Analysing Dispersion Portfolios

Having created a proxy for dispersion of beliefs, the first analysis to be undertaken is a portfolio analysis, as in DMS. The methodology of DMS follows the approach of Jegadeesh and Titman (1993), which sorted stocks into portfolios based on certain characteristics before the returns are analysed, in that case isolating the momentum anomaly. In the portfolio analysis stocks with a price less than five dollars are excluded so that results are not impacted by illiquid stocks. On the third Thursday of each month, the date on which IBES summary data is given portfolios will be created based on quintiles of dispersion. That is the first 20% of firms with the lowest level of dispersion will make up one portfolio and so on.

For each portfolio the equal weighted returns of all the stocks in the next calendar month will then be calculated from the CRSP database. Then this return can be compared across portfolios to see if returns vary systematically across them.

Continuing with these portfolios, different cuts of the data will be made to see how the anomaly varies across them. In particular, these will be made across time, as DMS showed that the anomaly was seemingly declining across time. Another important cut will be made across size. DMS found that the anomaly was stronger for small stocks, generally an indicator that arbitrageurs are exploiting the anomaly on large stocks. If it has declined more for larger stocks it will suggest that it is disappearing as arbitrageurs exploit it further, rather than as a result of it just being a statistical anomaly.

When sorting on size, a slightly different methodology will be used to that of DMS. DMS sorts stocks into quintiles based on market capitalisation, and then within these quintiles, sorts stocks again into further quintiles based on dispersion. This has the effect of reducing the importance of absolute dispersion, for example if large stocks have a lower dispersion then those stocks in the highest dispersion quintile amongst the largest stocks have a considerably lower average dispersion than those in the highest dispersion quintile for other sizes. This paper on the other hand, will form portfolios based on the absolute characteristics on both dispersion and market capitalisation. For example, the portfolio of the largest quintile of stocks and the highest quintile of dispersion will be comprised of the stocks with the highest level of dispersion out of all stocks, and which are also amongst the largest of all stocks. Not doing it this way makes it more challenging to interpret whether the results across different sizes of firm stem from less dispersion or weaker short sale constraints. The only downside is that it will reduce the sample size of some portfolios, for example there are less stocks in the largest size / highest dispersion group than in the smallest stocks / highest dispersion groups as on average smaller stocks have higher dispersion.

There will be one cut that more closely follows the methodology of DMS on a size basis, and that is a portfolio of the top 500 stocks based on market capitalisation, which is then split into portfolios based on the rank of dispersion amongst the top 500 stocks. It is important to note that the total number of firms in all five portfolios will not be 500. The aim of this analysis is to test the anomaly on the largest, most liquid stocks, where it would be easiest and most profitable to exploit it. Therefore, only the 500 largest stocks by market capitalisation in the CRSP database are included, and these then may be excluded for other reasons, such as having a price below five dollars or having less than two analyst forecasts in a given month.

Generating a Long-Short Portfolio

What is particularly interesting following the development of the portfolios based on dispersion is the long-short portfolio. This is a self-financing portfolio that, in any given month, is long the 20% of stocks with the lowest level of dispersion and short the 20% of stocks with the highest level of dispersion. This gives an indication of the profits that could be generated by a strategy trading on the Miller hypothesis and will allow for more detailed analysis of the anomaly.

Analysing the Long-Short Portfolio

Having generated the long-short portfolio it is possible to conduct a regression analysis on it. This allows for controls over the well documented common risk factors of the CAPM (Sharpe, 1964), the Fama-French three factor model (Fama and French, 1993, pp. 7 - 10) and the Carhart four factor model (Carhart, 1997, p. 61) to see if there are still excess returns having controlled for these factors. Beyond these common risk factors, the portfolio will also be tested against a more recent trading anomaly, the Betting Against Beta anomaly (Frazzini and Pedersen, 2014). This factor seems particularly relevant as the high dispersion portfolio has a higher beta than the low dispersion portfolio (see appendix 1 and 2) and so any excess returns could just be a manifestation of the Betting Against Beta anomaly.

Alongside this the long-short portfolio can provide interesting indications of the strength of the anomaly over time and the cumulative returns that could have been generated by trading on it.

Creating a Long – Short Portfolio Hedged Against Market Risk

It is also possible to hedge the strategy against market risk, in order to attempt to more accurately see the isolated returns of the anomaly. The methodology for this follows that of Bouchaud et al. (2016, p. 29). Firstly, the market beta of the long-short portfolio is estimated by undertaking a rolling regression of the long-short returns on the return of the market over the last 24 months. Then for each dollar of long position, a short position is taken on the market equal to the market beta.

Data

Sources of Data

IBES Database

The number of analyst forecasts, the mean forecast, and the standard deviation of forecasts were obtained from the IBES Unadjusted Summary History database. As noted in DMS (2002, p. 2117), the Adjusted database is not suitable for the analysis due to a rounding error during the adjustment process. Alongside this, they also note some discrepancies when calculating summary statistics manually, but this does not have a material impact on their results. Therefore, this paper will also use the Unadjusted Summary History database rather than the Detail History database.

CRSP Database

Returns and prices on individual stocks are obtained from the Center for Research in Security Prices dataset.

Stock Return Factors

For the regression tests of returns commonly used factors in the finance literature were obtained for use as controls. The Market Risk Premium, Size, Value, and Momentum factors were obtained from Ken French's website[3] via Wharton Research Data Services for the purpose of this analysis. The Betting Against Beta factor was obtained from the AQR Capital Management, LLC data library[4].

[3] Ken French's Data Library: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[4] AQR Capital Management Data Library: https://www.aqr.com/Insights/Datasets

Overview of Data

Table 1 gives a brief overview of the dataset used for this analysis. The sample of eligible stocks is considerably smaller than that of all CRSP stocks due to requirements of the analysis, such as there being more than two analyst forecasts in a given month so that dispersion can be calculated. Therefore, around 30% of CRSP stocks are eligible at any given time, though the proportion is even lower pre 1982, which is one reason why the analysis will be undertaken from 1983 onwards, in line with DMS. As also noted in DMS (2002, pp. 2118 – 2119), “eligible” stocks are on average considerably bigger than the average of all CRSP stocks. Interestingly, this difference has been narrowing as time has progressed. Whereas the average eligible stock had a market capitalisation 2.5 times the average CRSP stock in December 1982, it was just 1.9 times in June 2018. The mechanism for this change is unclear and beyond the scope of this paper, though it could potentially be caused by an increase in the number of analysts covering small stocks or from public stocks becoming larger on average and therefore more likely to be covered by analysts. It is, however, good for the results of this paper as it reduces the possibility that the results are just picking up a size effect.

The sample used by this paper also broadly matches that of DMS, with some small variations in the number of stocks and the average size, though these are not material differences, and as will be shown later, the results from the period in DMS are replicated closely.

Table 1

Database Summary Statistics: December 1976 to June 2018

This table gives an overview of the datasets used in the analysis. On the left-hand side is an overview of the entire CRSP database, whilst the right-hand side gives an overview of "eligible" stocks. An "eligible" stock is one with a price greater than 5, that has two or more analyst forecasts in the month. DMS data is from Diether et al. (2002, p. 2119) and refers to the time period in the row above.

Summary Statistics for 1976 - 2018						
	All CRSP Stocks			Eligible Stocks		
Date	Number of Firms	Mean Size (Millions)	Percentage of Firms Eligible	Number of Firms	Mean Size (Millions)	Mean No. of Estimates
12/1976	4,998	193.2	14.1%	703	952.0	7.88
12/1982	5,466	300.2	30.9%	1,691	759.6	8.83
DMS	*5,438*	*305.6*	*31.9%*	*1,735*	*766.0*	*8.78*
12/1988	6,921	397.4	29.7%	2,056	1,090.1	9.77
DMS	*6,798*	*408.6*	*34.0%*	*2,309*	*1,094.1*	*9.82*
12/1994	8,134	628.5	34.7%	2,826	1,388.3	8.12
DMS	*8,029*	*633.8*	*40.7%*	*3,269*	*1,423.9*	*8.26*
12/2000	8,107	1,986.0	31.2%	2,533	4,332.7	7.51
DMS	*7,823*	*2,032.9*	*40.5%*	*3,166*	*4,740.6*	*7.79*
12/2006	6,797	2,997.6	37.4%	2,541	4,932.2	8.00
12/2012	6,614	3,213.5	32.7%	2,164	6,001.9	9.45
06/2018	7,334	5,162.7	30.6%	2,241	9,861.4	8.91

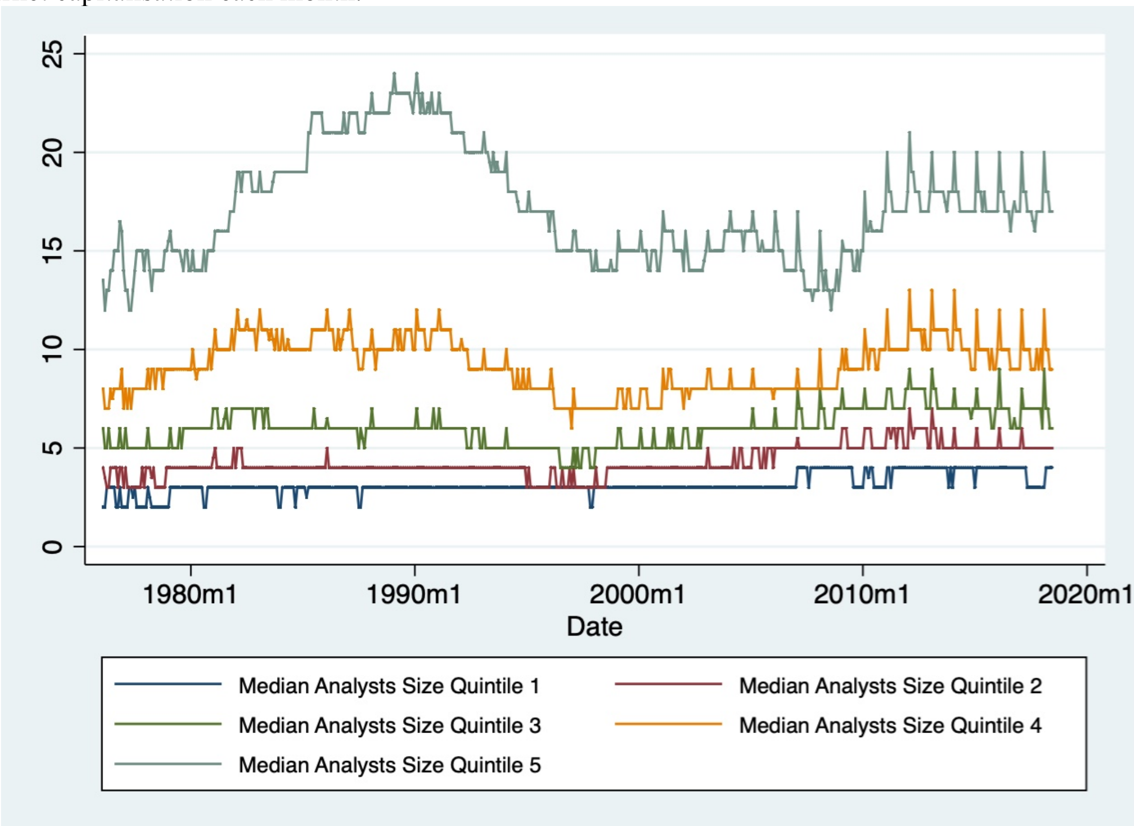
Analyst Coverage

Figure 1 shows the depth of analyst coverage in equity markets. As expected, the depth of coverage is much higher for larger stocks, likely driven by greater demand for analysis on these stocks. Interestingly, coverage for smaller stocks appears to have remained broadly constant, with a slight increase since 2010. Also, of interest is that coverage increased greatly in the 1980s, peaking at around 1990, before falling back to previous levels. The mechanism behind this is unclear, but it is interesting that it coincided with a fall in dispersion, which has also increased since 2010, at the same time there has been a slight increase in analyst coverage. Finally, there appears to be some seasonality to analyst coverage, which is likely connected to the seasonality around earnings announcements and this seasonality has somewhat increased in recent years.

Figure 1

Median Analyst Coverage by Size of Company Through Time

This chart shows the median analysts covering stocks in each market capitalisation quintile for each month since February 1976. The market capitalisation quintiles are created by ranking each stock by market capitalisation each month.



Dispersion

Whilst the focus of this paper is on the Miller hypothesis in the real world, dispersion of beliefs in the stock market is an area that has received relatively little attention. Therefore, the behaviour of dispersion will be briefly analysed, both on a firm and aggregate level to see what insights could be relevant for future research.

Firm Level: Dispersion with Distance to Results

A first interesting angle is how, on a firm level, dispersion in analyst forecasts varies with the amount of time until actual results are announced.

Figure 2 shows this for three different time periods: 1983 – 1992, 1993 – 2001, 2002 – 2018. This seemingly tells an interesting story. The first thing to note is the behaviour of dispersion in the two periods from 1992 onwards. Whilst conventional wisdom would suggest that the closer to results you are the more clarity there is and therefore the lower dispersion is, there seems to be at least two processes at work. This process seems to dominate when there is approximately 250 days to the results, but before this dispersion actually increases. One potential mechanism for this is that a long way from results is actually just after the previous results have been announced, which provides an extremely clear signal on the status of the business to analysts. As the distance from this signal increases there are other noisier signals, which leads to dispersion increasing until the first affect begins to dominate, thus reducing dispersion.

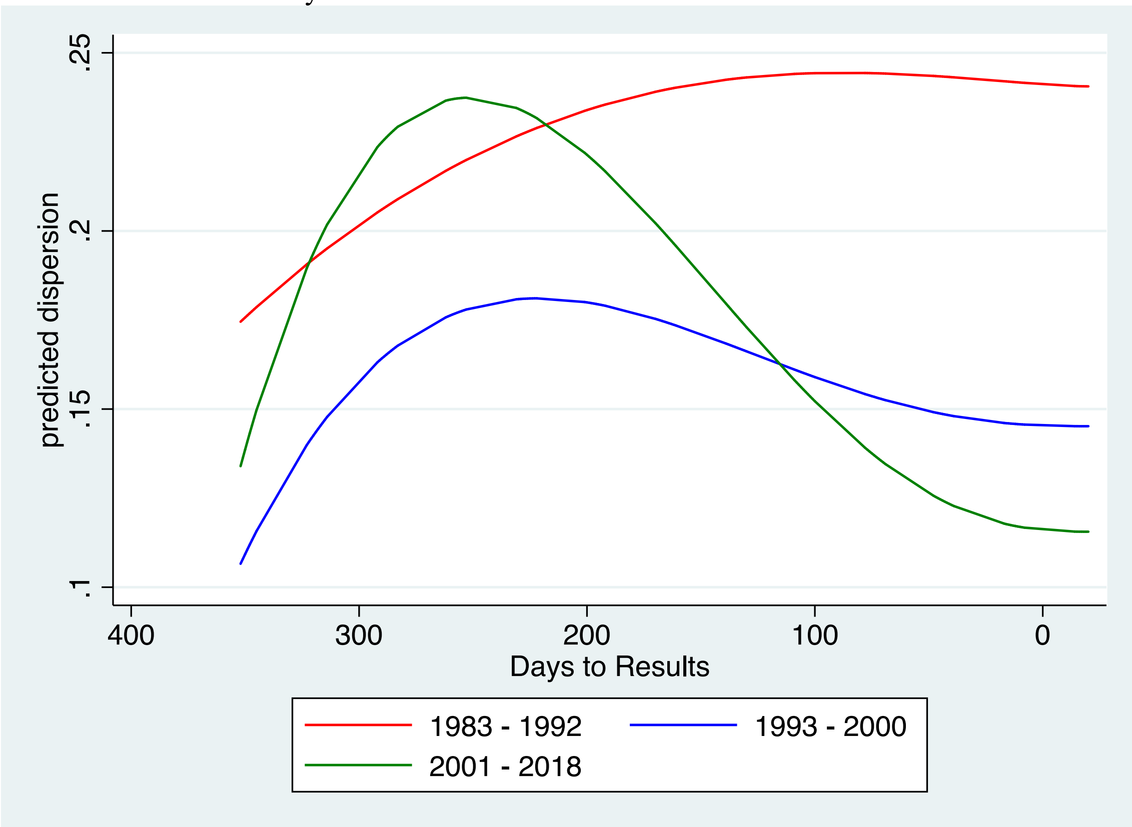
A clear potential factor driving the decrease in dispersion closer to the announcement date would be earnings guidance. As is shown in research by the management consultancy McKinsey and Company (Hsieh et al, 2006) the prevalence of earnings guidance greatly increases in the 1990s. In fact, of companies with revenue over $500 million, the number of companies providing earnings guidance grew from 94 in 1994 to approximately 1,200 in 2001. That data analysed in figure 2 shows that in the period from 1983 to 1991 dispersion grew steadily from the previous announcement to a peak just before the next announcement. This suggests that the growth of earnings guidance has had a significant impact on dispersion, an effect documented in other papers including Chen et al. (2011, p. 148) and Houston et al. (2010, p. 177).

Whilst looking into this further is beyond the scope of this paper, this demonstrates the interesting mechanisms at play. As the Miller hypothesis seems to be leading to significant mispricing in markets and earnings guidance is a greatly debated topic, this could provide for an interesting contribution to the debate.

Figure 2

Variation in Dispersion with Days to Results

This chart shows the equal weighted mean dispersion in analyst forecasts across the number of days until the earnings results are announced. The prediction is based on a polynomial regression of equal weighted average dispersion on the number of days to results. Dispersion is calculated as the standard deviation in analyst forecasts divided by the absolute value of the mean analyst estimate. The time period of data is from January 1983 to June 2018.



Aggregate Level: Dispersion over Time

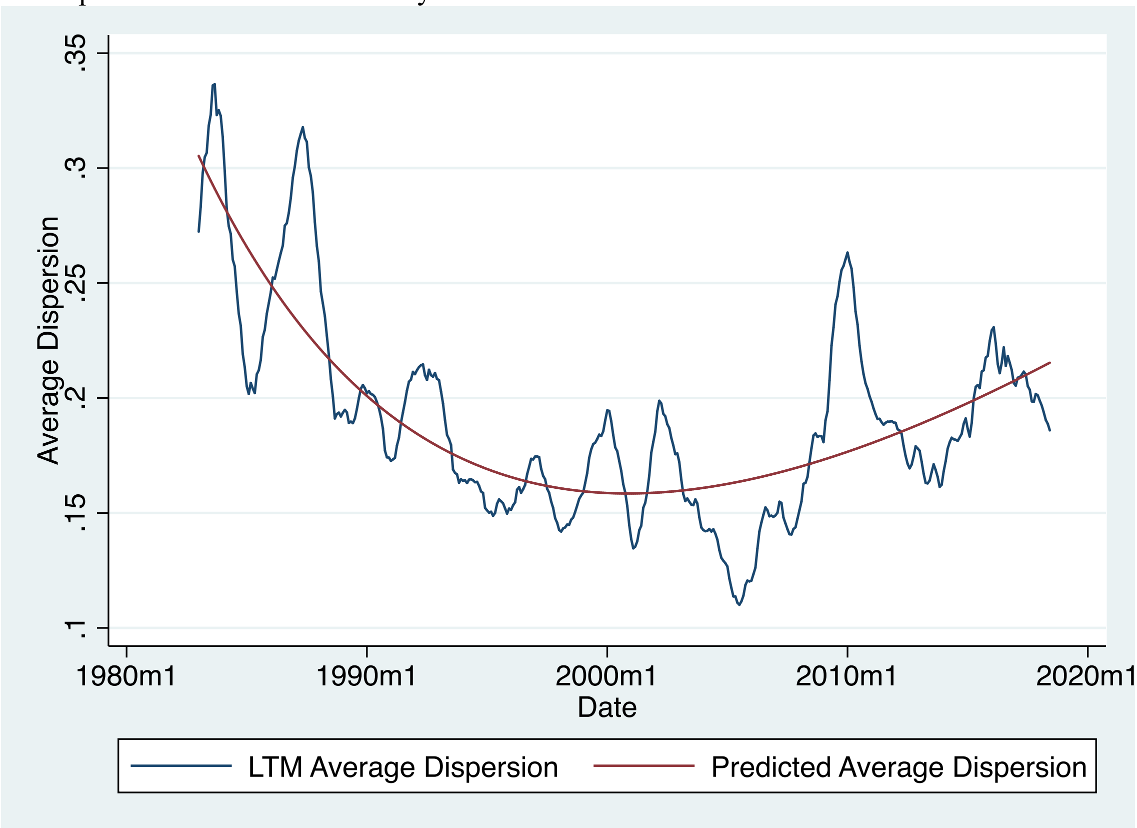
As shown in figure 3, aggregate level dispersion is highly variable over time, susceptible to peaks and troughs. In particular it was high in the 1980s, before it steadily declined until 2005. Recent years have seen somewhat of a rebound including, in the aftermath of the financial crisis, to levels not seen since the 1980s. Overall, however, the recent period has seen levels of dispersion in analyst forecasts more like those in the early 1990s.

Again, the reasons for this are unclear, though the increase in earnings guidance in the 1990s is likely to be one of the factors reducing average disagreement in that period. Alongside this it was also the period of the "great moderation" with a relatively stable macroeconomic environment that to an extent disappeared after 2008, which has been accompanied by an increase in average dispersion.

Figure 3

Average Dispersion Over Time

This chart shows the equal weighted mean dispersion in analyst forecasts across time. The prediction is based on a quadratic regression of equal weighted average dispersion on time. Dispersion is calculated as the standard deviation in analyst forecasts divided by the absolute value of the mean analyst estimate. The time period of data is from January 1983 to June 2018.



Results

Portfolio Analysis

The first set of results to be analysed will be those based on the basic portfolio analysis outlined in the methodology.

Comparison to DMS

Before delving into the portfolio analysis results in greater detail, as this paper is based on DMS and broadly follows the methodology of that paper especially on the portfolio analysis, it is important to first compare the results between DMS (2002, p. 2121) and this paper. As is shown in table 2 the results from the same time periods are extremely similar; they are all within a reasonable margin of error. The trend also closely matches that of DMS (2002, p. 2133), with falling returns on the long-short portfolio, to the extent it was no longer significant.

Table 2

Comparison of Portfolio Analysis Results to DMS

This table gives a high-level comparison of the results in this paper to those in DMS. The results are for the period from February 1983 to December 2000. The portfolio results are generated by dividing stocks into five quintile portfolios based on the dispersion in analyst forecasts on the third Thursday of the month. The portfolio returns are for the next calendar month and are equal weighted. Standard errors are adjusted for autocorrelation using the Newey-West method with a 12-month lag.

	DMS Results	This Paper	% Difference
Dispersion Quintiles			
D1 (Low)	1.48	1.47	(0.7%)
D2	1.36	1.38	1.5%
D3	1.23	1.25	1.6%
D4	1.12	1.13	0.9%
D5 (High)	0.69	0.71	2.9%
D1-D5	0.79***	0.75**	(5.1%)
t-statistic	*(2.88)*	*(2.49)*	
Sub-period Analysis (D1 - D5)			
1983 - 1991	1.16***	1.12***	(3.4%)
t-statistic	*(4.63)*	*(4.54)*	
1992 - 2000	0.41	0.39	(4.9%)
t-statistic	*(0.86)*	*(0.76)*	

*** p<0.01, ** p<0.05, * p<0.1

Further Portfolio Results

Having now generated results comparable to those found by DMS, the behaviour of the portfolio results will be looked at in further detail. In particular, a key question is how the results vary as the size of the firm varies. For this dispersion portfolios will also be generated across size quintiles, to see how average returns vary on a cross tabulation of dispersion and size.

Table 3 presents these results in significant detail. Firstly, mean returns across dispersion and size portfolios from 1983 to June 2018 are presented, which are also accompanied by the mean returns of the long-short portfolio across these periods. Then the mean returns of the long-short portfolio are segmented across four time periods from 1983. The first two broadly match those in DMS, whilst the next two are based on entirely new data. Finally, the mean dispersion in the highest and lowest dispersion portfolios is compared across time periods. The size-based results do diverge somewhat from DMS due to the slight methodology change noted earlier in this paper. It primarily results in the average level of dispersion in the top dispersion portfolio not declining as significantly as the size quintile increases.

This provides some highly interesting insights. As noted in DMS (2002, pp. 2132 – 2133) the mean returns of the anomaly were declining across the time period they analysed. With regards to the Miller hypothesis, this could have been as a result of weakening short sale constraints, or falling dispersion of beliefs, or some combination of the two. This trend continued in the period from 2001 – 2009, with the significance of returns almost completely disappearing across all size portfolios. Interestingly, however, this trend has since been reversed since 2010, with some level of significance of returns to the strategy in all size portfolios. Whilst again this could be either as a result of increasing dispersion or increasing short sale constraints, or a combination of the two. The average dispersion of the highest dispersion portfolio has increased slightly across all size portfolios, which has also been documented previously in figure 3, suggesting changes in the level of dispersion, rather than short sale constraints are driving these results.

Table 3

Portfolio Analysis Across Dispersion, Size, and Time

This table gives detailed results for the portfolio analysis. The portfolio results are generated by dividing stocks into five quintile portfolios based on the dispersion in analyst forecasts on the third Thursday of the month. The portfolio returns are for the next calendar month and are equal weighted. Standard errors are adjusted for autocorrelation using the Newey-West method with a 12-month lag. The time period of data is from January 1983 to June 2018. Top 500 are the results for the 500 firms with the highest capitalisation in the CRSP database in any given month.

Mean Returns							
	Size Quintiles						
	S1 (Small)	S2	S3	S4	S5 (Large)	Top 500	All Stocks
Dispersion Quintiles							
D1 (Low)	1.40	1.41	1.29	1.24	1.08	1.12	1.26
D2	1.37	1.27	1.23	1.06	1.09	1.03	1.18
D3	1.17	1.10	1.11	1.03	1.03	1.11	1.08
D4	0.85	1.01	1.03	1.04	1.01	1.08	0.98
D5 (High)	0.47	0.60	0.72	0.84	0.80	0.84	0.64
D1 - D5	**0.93*****	**0.81*****	**0.57****	**0.40**	**0.28**	**0.28**	**0.63*****
t-statistic	(4.97)	(3.70)	(2.53)	(1.58)	(1.05)	(1.22)	(3.06)
Sub-Period Analysis (D1-D5)							
1983 - 1991	**1.31*****	**1.37*****	**1.13*****	**0.93****	**0.51**	**0.53***	**1.13*****
t-statistic	(4.87)	(5.29)	(4.79)	(2.50)	(1.40)	(1.66)	(4.64)
1992 - 2000	**1.13****	**0.45**	**0.18**	**-0.10**	**-0.16**	**0.13**	**0.39**
t-statistic	(2.61)	(0.85)	(0.30)	0.15	0.26	(0.26)	(0.76)
2001 - 2009	**0.73***	**0.58**	**0.15**	**0.18**	**0.27**	**0.02**	**0.34**
t-statistic	(1.89)	(1.23)	(0.34)	(0.34)	(0.42)	(0.04)	(0.79)
2010 - 2018	**0.53****	**0.83****	**0.84*****	**0.61****	**0.52***	**0.44**	**0.64****
t-statistic	(2.01)	(2.52)	(3.65)	(2.53)	(1.77)	(1.66)	(2.60)

Mean Dispersion							
	1983 - 1991						
D1 (Low)	0.010	0.014	0.016	0.018	0.018	0.017	0.016
D5 (High)	0.939	0.949	0.975	1.039	0.777	0.524	0.948
	1992 - 2000						
D1 (Low)	0.006	0.008	0.009	0.010	0.011	0.010	0.009
D5 (High)	0.754	0.651	0.625	0.594	0.681	0.413	0.672
	2001 - 2009						
D1 (Low)	0.007	0.008	0.008	0.009	0.009	0.007	0.008
D5 (High)	0.722	0.732	0.645	0.615	0.582	0.361	0.676
	2010 - 2018						
D1 (Low)	0.008	0.009	0.010	0.010	0.009	0.007	0.009
D5 (High)	0.807	0.875	0.805	0.711	0.734	0.365	0.801

Long – Short Portfolio

Having looked broadly at average returns in the portfolio strategy analysis the long-short portfolio will now be analysed in greater detail, including controlling for common risk factors to gain further insights into the anomaly.

Cumulative Returns to the Long-Short Portfolio

Firstly, it is clear that the long-short portfolio has generated significant returns, especially when looking at it from when this paper's analysis begins in 1983. As figure 4 demonstrates this strategy has generated significant returns, with one dollar invested in 1983 being worth approximately $10 in 2018. This does, however, hide significant variations in returns to the strategy, as has been shown in the portfolio analysis. Whilst the strategy generated significant and steady returns from 1983 to 1998, the period after that was significantly more turbulent. Post-1998 the strategy performed poorly, coinciding with the dot-com crash, before recovering strongly. A flat performance followed, albeit with a couple of peaks, followed by crashes until previous 1998 highs were reached in 2011 and the strong performance of the strategy returned in recent years.

Interestingly, when looking at the poor performance in 1999 it is hugely driven by the performance of the high dispersion stocks. As these stocks are sold short, returns will be generated if they perform badly. In this period, they consistently performed extremely well, with very high returns. It seems that this was a function of the dotcom crash, and the explanation it lends itself to is that there was a lot of disagreement over the stocks that were performing extremely well in this period, however instead of the overvaluation resulting in lower performance in the future they continued to go up and up. This is likely due to a complete decoupling of performance from fundamentals at that time leading to a breakdown of the Miller hypothesis. In a sense, instead of the stock performing badly the month after having high dispersion, there was just more optimists pushing the price and returns up.

To analyse the performance of the long-short portfolio in further detail some key metrics can be analysed. The risk – return trade-offs of the portfolio can be captured by the Sharpe ratio, which compares average returns per unit of risk (represented by the standard deviation of returns), the formula of the Sharpe ratio is shown below. Note that as this is a self-financing portfolio it does not include the risk-free rate.

$$Sharpe\ Ratio = \frac{annualised\ return\ of\ strategy}{anualised\ standard\ deviation\ of\ strategy}$$

Overall, taking all observations since 1983, this strategy has a Sharpe ratio of 0.58, an indication that this strategy has had a reasonable performance relative to its risk. The annualised return on this portfolio is 7.0%, and the negative skewness shows a long tail of negative returns, of which the 1999 crash for the strategy is demonstrative of.

Then analysing the long-short portfolio hedged against the market returns, it is possible to see that the returns of the strategy are even stronger than displayed in figure 4. In fact, taking the logathrimic returns in figure 5 to smooth the exponential feature of returns demonstrates that this strategy has generated steady returns over nearly the entire period since 1983, though the clear crash in 1999 is still significant. This crash stands out as the major failing of this strategy over the entire period. When hedging the market risk, it also seems that the anomaly actually exists strongly over the 2001 – 2009 period, unlike the portfolio analysis, which suggested otherwise.

More formally, the hedged long-short strategy has generated an annualised return of 9.6%, with an improved Sharpe ratio of 0.96, though the negative skewness of returns has actually increased relative to the unhedged portfolio, and the kurtosis has increased, showing a prevalence of extreme values in this strategy.

Finally, as in the portfolio analysis previously, a specific long-short portfolio for the largest 500 stocks by market capitalisation was created. As expected, the annualised returns to this strategy were considerably lower, at 2.3%, with a much lower Sharpe ratio of 0.15, showing a less appealing risk – return trade off compared to the market as a whole.

Figure 4

Cumulative Returns of Long-Short Strategy

This chart shows the cumulative returns of a strategy that is short the quintile of stocks with the highest dispersion, based on dispersion in analyst forecasts on the third Thursday of the previous month, and long the quintile with the lowest dispersion. The time period of data is from January 1983 to June 2018.

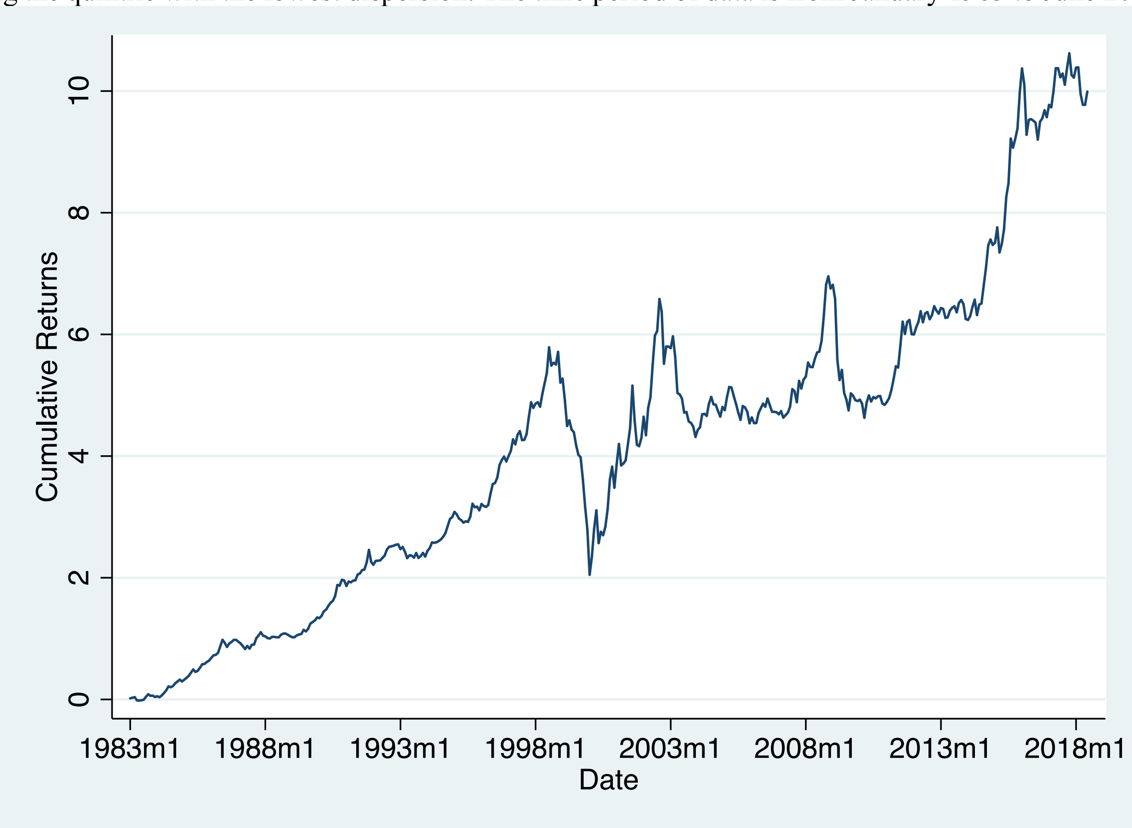


Table 4

Summary of Return Profiles of Hedged and Non-Hedged Long-Short Strategies

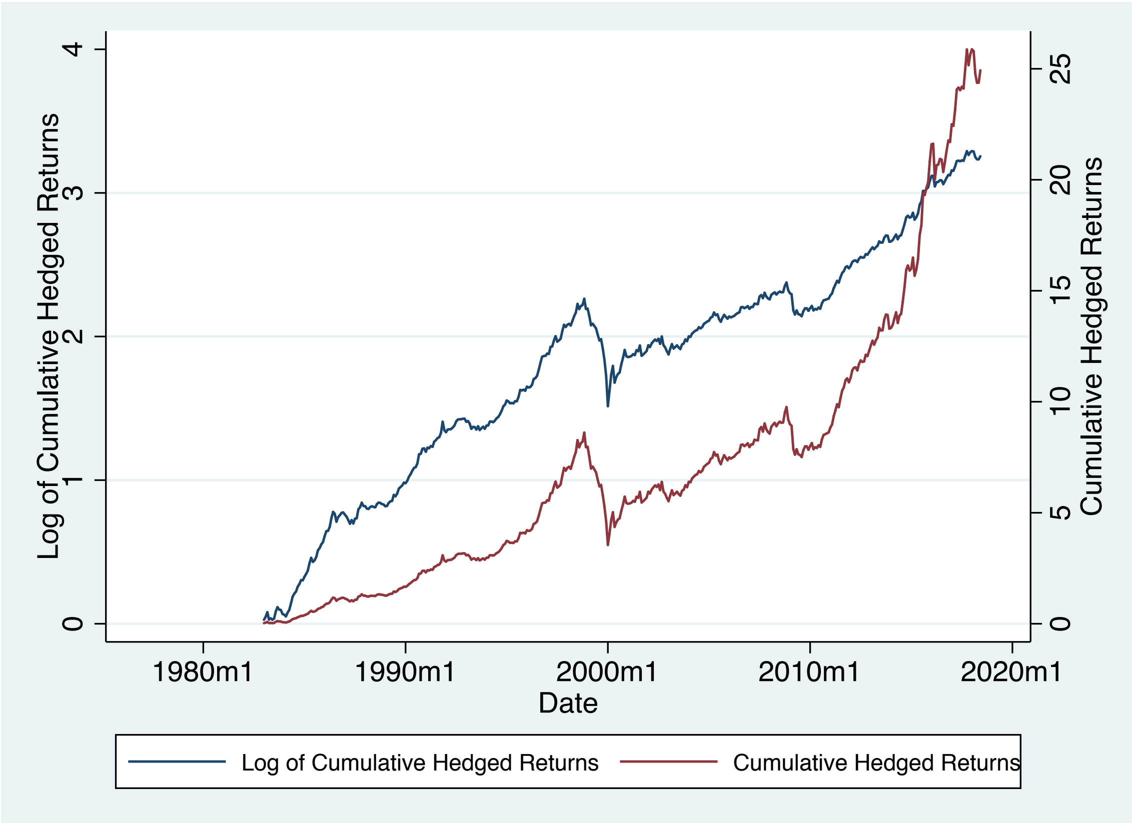
This table shows the key summary statistics of a strategy that is short the quintile of stocks with the highest dispersion, based on dispersion in analyst forecasts on the third Thursday of the previous month, and long the quintile with the lowest dispersion. The hedged strategy is hedged each month against the market return by going short the beta the portfolio has with the market for every dollar invested long. The beta of the portfolio is estimated over the previous 24 months of returns. The long-short strategy is that which only includes the 500 largest stocks by market capitalisation in the CRSP database each month. The time period of data is from January 1983 to June 2018.

	Annualised Return (%)	Annualised Standard Deviation (%)	Sharpe Ratio	Mean (%)	Skewness	Kurtosis	Max (%)	Min (%)
Long-Short Strategy	7.00	12.01	0.58	0.63	-0.69	7.63	13.76	-19.61
Hedged Long-Short Strategy	9.63	10.07	0.96	0.81	-1.13	9.65	11.89	-18.93
Long-Short Top 500 Stocks	2.28	14.75	0.15	0.28	0.05	6.28	18.57	-21.79

Figure 5

Cumulative Returns (Raw and Logarithmic) of Market Neutral Long-Short Strategy

This chart shows the cumulative returns of a strategy that is short the quintile of stocks with the highest dispersion, based on dispersion in analyst forecasts on the third Thursday of the previous month, and long the quintile with the lowest dispersion. The portfolio is then hedged each month against the market return by going short the beta the portfolio has with the market for every dollar invested long. The beta of the portfolio is estimated over the previous 24 months of returns. Alongside this is the logarithm of the cumulative returns of the hedged strategy. The time period of data is from January 1983 to June 2018.



Multi-Factor Time Series Tests

As discussed in the methodology section, it is important to model the returns of the long-short strategy, whilst controlling for the common risk factors in the finance literature. Whilst the previous analysis gives broad indications of the strategy, a regression analysis will allow for more formalised results. Table 5 presents these results for every month since the beginning of 1983.

Across all the regressions the alpha, a measure of excess returns not explained by the risk factors, is large, and highly significant. This indicates that common proxies for risk cannot explain the returns from the dispersion strategy, implying that there is some level of mispricing in the market and that an anomaly clearly exists

Table 6 goes on to segment these results by time period using a dummy variable to compare time period against a default of 1983 – 1991, when it was clear that the anomaly was strong. In fact, the anomaly seems to have been broadly as strong across all time periods, with potentially a slight weakening of the alpha from 1992 – 2009, though this is only significant at the 10% level. This time period also includes the exceptional crash in 1999, a unique event for the strategy across the entire time period. This confirms the results seen when the long-short portfolio was hedged against the market returns, and demonstrates the weakness of the basic portfolio analysis.

Table 7 goes on to analyse the results for the portfolio comprised of the 500 stocks with the highest market capitalisation. Here, the direction of results is as expected with a smaller alpha, indicating that the strategy is generating lower excess returns. It is surprising that this alpha is significant at the 5% level in the first four models, as these stocks would likely have lower short sale constraints, and potentially lower dispersion. Despite this, the importance of including the Betting Against Beta factor is demonstrated as driving the alpha for these largest stocks, and it is actually insignificant once including this factor. Including Betting Against Beta for all stocks does also weaken the alpha, but it still remains highly significant with a t statistic greater than 3.

Though not directly relevant for the analysis, appendix 1 and 2 add some credibility to results. They demonstrate that the highest dispersion portfolio has unexplained returns, shown by a highly significant negative alpha. The returns of the lowest dispersion portfolio, on the other hand, are completely explained by common risk factors, once controlling for the Betting Against Beta anomaly. This is consistent with the Miller hypothesis as it implies that stocks with high dispersion are overvalued, but stocks with low dispersion are correctly valued.

Table 5

Time-Series Tests of the Long-Short Portfolio Using the Carhart Four Factor Model and Betting Against Beta

This table shows time series regressions of a strategy that is short the quintile of stocks with the highest dispersion, based on dispersion in analyst forecasts on the third Thursday of the previous month, and long the quintile with the lowest dispersion. The Market Risk Premium, Small Minus Big, High Minus Low and Up Minus Down factors are those calculated by Kenneth French. Betting Against Beta is the factor calculated by AQR Capital Management, LLC. Standard errors are adjusted for autocorrelation using the Newey-West method with a 12-month lag. The time period of data is from January 1983 to June 2018.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
MRP	-0.37***	-0.28***	-0.28***	-0.22***	-0.21***
	(-5.13)	(-4.19)	(-4.37)	(-5.02)	(-6.05)
SMB		-0.56***	-0.55***	-0.56***	-0.54***
		(-5.39)	(-6.33)	(-5.09)	(-6.50)
HML			0.07	0.15*	0.02
			(0.67)	(1.68)	(0.19)
UMD				0.22***	0.15**
				(3.00)	(2.06)
BAB					0.24**
					(2.57)
Constant	0.88***	0.86***	0.84***	0.67***	0.51***
	(4.71)	(4.94)	(4.96)	(4.47)	(3.40)
Observations	426	426	426	426	425

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6

Time-Series Tests of the Long-Short Portfolio Using the Carhart Four Factor Model Segmented by Time Period

This table shows time series regressions of a strategy that is short the quintile of stocks with the highest dispersion, based on dispersion in analyst forecasts on the third Thursday of the previous month, and long the quintile with the lowest dispersion. The Market Risk Premium, Small Minus Big, High Minus Low and Up Minus Down factors are those calculated by Kenneth French. Betting Against Beta is the factor calculated by AQR Capital Management, LLC. Standard errors are adjusted for autocorrelation using the Newey-West method with a 12-month lag. The time period of data is from January 1983 to June 2018.

VARIABLES	(1) All Stocks	(2) Largest 500
MRP	-0.22***	-0.25***
	(-5.88)	(-4.77)
SMB	-0.54***	-0.56***
	(-6.42)	(-5.43)
HML	0.02	-0.05
	(0.28)	(-0.34)
UMD	0.15**	0.07
	(2.13)	(0.90)
BAB	0.24**	0.30**
	(2.58)	(2.37)
1992 - 2000	-0.67*	-0.27
	(-1.67)	(-0.54)
2001 - 2009	-0.56*	-0.33
	(-1.89)	(-0.60)
2010 - 2018	-0.19	0.17
	(-0.67)	(0.46)
Constant	0.87***	0.30
	(3.81)	(0.90)
Observations	425	425

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7

Time-Series Tests of the Long-Short Portfolio for the Top 500 Stocks by Market Capitalisation

This table shows time series regressions of a strategy that is short the quintile of stocks with the highest dispersion, based on dispersion in analyst forecasts on the third Thursday of the previous month, and long the quintile with the lowest dispersion. Only the 500 largest stocks by market capitalisation in any given month are considered. The Market Risk Premium, Small Minus Big, High Minus Low and Up Minus Down factors are those calculated by Kenneth French. Betting Against Beta is the factor calculated by AQR Capital Management, LLC. Standard errors are adjusted for autocorrelation using the Newey-West method with a 12-month lag. The time period of data is from January 1983 to June 2018.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
MRP	-0.39***	-0.30***	-0.29***	-0.26***	-0.25***
	(-4.48)	(-3.79)	(-4.06)	(-4.23)	(-4.81)
SMB		-0.59***	-0.58***	-0.58***	-0.57***
		(-4.23)	(-4.89)	(-4.38)	(-5.41)
HML			0.06	0.12	-0.05
			(0.39)	(0.84)	(-0.39)
UMD				0.15*	0.07
				(1.89)	(0.91)
BAB					0.31**
					(2.44)
Constant	0.54**	0.53**	0.51**	0.39**	0.18
	(2.54)	(2.41)	(2.53)	(2.05)	(0.88)
Observations	426	426	426	426	425

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Analysis

Interpreting the Results

As has now been thoroughly demonstrated, the anomaly hypothesised by Miller and empirically shown by DMS, appears to still exist in the data today. This is even when controlling for common risk factors, and a more recent, but strong anomaly, that of Betting Against Beta. The implications of these results rest on a major initial assumption, of whether the Miller hypothesis is true or false.

Evidence for the Miller Hypothesis

The data analysed provides further evidence to previous studies that suggests the Miller hypothesis is a correct interpretation of the behaviour of financial markets. Not only do the returns to a long-short strategy trading on the anomaly provide evidence, but also the fact that the unexplained portion of the strategy is on the short side (see appendix 1 and 2). It is the stocks that have high dispersion that will be overvalued, whilst those with low dispersion are "correctly" valued and this plays out in the evidence presented. Alongside this, the anomaly is concentrated amongst and driven by smaller stocks. It is likely these have higher short sale constraints, one of the key pillars of the theory, and so this finding is again consistent with the Miller hypothesis. Though this evidence does point toward the Miller hypothesis it could still be false, and therefore the analysis from this point will take two views, one assuming Miller is true, and one assuming it is false.

Miller is True: Dispersion of Beliefs vs. Short Sale Constraints

Assuming that the Miller hypothesis is correct then it is possible to hypothesise around its two central pillars: dispersion of beliefs and short sale constraints. For the anomaly to exist both of these pillars need to be present. It has been demonstrated that the anomaly is still present. Dispersion did experience somewhat of a decline in the period from 1994 – 2009, followed by a slight resurgence. Yet throughout this the anomaly has remained relatively intact, seeming to slightly follow the behaviour of dispersion. Therefore, it follows that short sale constraints must have also remained relatively constant throughout the entire period. Overall it is likely that if short sale constraints were to have become more relaxed throughout the period then the anomaly would have disappeared "on the margin", that is on the largest stocks where it exists and is most profitable to exploit. Instead, during the period in question, the anomaly has never existed in the largest stocks, yet has not disappeared among any other stocks. It may have been expected that short sale constraints would have declined throughout this period, with increasing completeness of financial markets. Indeed, this was implied by Figlewski and Webb (1993), who suggested options reduce short sale constraints. Despite this they do not appear to have fallen significantly. Drechsler and Drechsler (2014, pp. 38 - 42) provides some evidence for this, with the securities lending fee, a measure of the cost of shorting, on average being significant (not falling below 55 basis points per year since 2004), and relatively steady, apart from a very high peak in the 2008 financial crisis. An interesting area for future research would be integrating data on the cost of shorting into the analysis of this paper to see if, as predicted, the anomaly is stronger for those stocks with a higher shorting fee.

On the regulatory side, the SEC removed the uptick rule in 2007 (SEC, 2007), but it was then replaced in 2010 with a different version of the uptick rule that acts as a "circuit breaker" after a 10% price decline in one day (SEC, 2010). Assuming that "direct" costs of short selling have not fallen, yet also not increased, it then implies that "indirect" costs closely linked to the arguments of Schleifer and Vishny (1997) have not fallen either. A lack of understanding, a lack of willingness to absorb short term losses, and a plethora of uninformed investors in the market could all be driving short sale constraints, and thus the anomaly in this paper.

Miller is False: Explanations for the Anomaly

Alternatively, it could be assumed that the Miller hypothesis is, in fact, false, and something else entirely is driving the documented anomaly.

A conventional explanation in finance would be that dispersion is a proxy for some risk that investors face across stocks. Yet the argument of DMS (2002, p. 2139) remains, the sign is all wrong. High dispersion stocks have low returns, implying lower risk. It seems difficult to conceive of how dispersion could be proxying for a risk that is lower amongst stocks that have a high level of dispersion.

This leaves space for alternative explanations. Many papers, including Diamond and Verrechia (1987) and Cornelli and Yilmaz (2015) attempt to propose alternatives to Miller, yet their predictions do not hold up against the data, which finds systematic mispricing, and specifically systematic overpricing. Alternatively, it could be that a feature of the methodology to test the Miller hypothesis is flawed, maybe analyst forecasts are not a good proxy for dispersion, and there is some other factor driving these forecasts that also systematically drives returns. This is an area for future research into the anomaly to focus on to either disprove the Miller hypothesis, or to add credibility to it. Avramov et al. (2009) could provide a starting point into alternative explanations with its evidence that the anomaly is driven by financial distress, though there are questions over how the results for the aggregate market from Park (2005) and Yu (2011) can be explained by this. Another explanation from Johnson (2004) that the results can be explained by a general options result are interesting, but then it would seem likely that the result would then exist across all sizes of firm, rather than just being concentrated in the smallest firms, which likely have the highest short sale constraints.

Earnings Guidance

As was briefly touched upon on page 14, there is initial evidence for a link between dispersion in analyst forecasts and the prevalence of earnings guidance. Earnings guidance is a much-debated topic, and while there is a plethora of arguments, the impact of earnings guidance on accurate valuation through the mechanism of dispersion of beliefs should not be ignored.

Implications for the Replication of Results Based on IBES Estimates

Finally, and importantly, a key implication for future research stems from the successful replication of the results of DMS. Ljungqvist et al (2007) had raised concerns that adjustments to historical IBES data could damage research by reducing the accuracy of data as it was when the IBES data was first published. By closely reproducing the results of DMS, this paper has helped to allay some of the fears raised. Though there may have been adjustments to the database, the key findings of research remain the same, something of vital importance for credibility of both past and future research.

Conclusion

To summarise the results and analysis in this paper, it has been found that the anomaly proposed by Edward Miller is still found in US equity markets today, as strongly as it existed in the 1980s. The key finding is that a long-short strategy based on the anomaly generates excess returns of 0.51% per month, beyond those explained by the Carhart four factor model and the Betting Against Beta anomaly, is an interesting contribution to the debate around the efficient markets hypothesis.

There is plenty of space for further research into this area, especially with short sale constraints seemingly creating such a significant impediment to a well-functioning equity market. Though there is significant support for Miller's theory, it is still a theory with considerable debate around it. Whether it is the empirical findings of Avramov et al. (2009) that financial distress appears to supersede disagreement as an explanation for the anomaly or the theoretical paper of Nezafet, Wang, and Schroder (2017), which incorporates endogenous information gathering into a theory of disagreement and short sale constraints, there is plenty of space for future research. Going forward, with solid evidence for Miller, papers such as these should form the basis of research, in order drive financial theory forward, as either further evidence will be generated in support of Miller or a new theory will emerge to explain empirical findings.

Finally, and more generally, this paper shows how important disagreement is in the behaviour of financial markets, so any future research into disagreement can generate interesting insights that may have been previously neglected. Disagreement seems to have had major trends through the years, which on first inspection has some correlation to the depth of analyst coverage. What, if anything is driving disagreement and this relationship is another question for future research.

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Appendix

Appendix 1

Time-Series Tests of the Dispersion Portfolio Returns Using the Carhart Four Factor Model and Betting Against Beta

This table shows time series regressions of the highest (5) and lowest dispersion (1) portfolios, based on dispersion in analyst forecasts on the third Thursday of the previous month, and long the quintile with the lowest dispersion. The Market Risk Premium, Small Minus Big, High Minus Low and Up Minus Down factors are those calculated by Kenneth French. Betting Against Beta is the factor calculated by AQR Capital Management, LLC. Standard errors are adjusted for autocorrelation using the Newey-West method with a 12-month lag. The time period of data is from January 1983 to June 2018.

	(1)	(2)	(3)	(4)
VARIABLES	Dispersion Portfolio 1	Dispersion Portfolio 1 incl. BAB	Dispersion Portfolio 5	Dispersion Portfolio 5 incl. BAB
MRP	0.95***	0.95***	1.17***	1.17***
	(39.90)	(55.59)	(43.77)	(46.92)
SMB	0.36***	0.37***	0.92***	0.91***
	(3.66)	(4.68)	(33.53)	(34.52)
HML	0.17**	0.07	0.02	0.05
	(2.38)	(1.42)	(0.54)	(0.95)
UMD	0.00	-0.05	-0.21***	-0.20***
	(0.08)	(-1.03)	(-7.43)	(-6.15)
BAB		0.19***		-0.06
		(3.70)		(-1.16)
Constant	0.24***	0.12	-0.43***	-0.39***
	(2.90)	(1.42)	(-4.78)	(-4.18)
R-Squared	90.50%	92.19%	94.44%	94.52%
Observations	426	425	426	425

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 2

Time-Series Tests of the Dispersion Portfolio Returns Using the Carhart Four Factor Model and Betting Against Beta for 500 Largest Stocks

This table shows time series regressions of the highest (5) and lowest dispersion (1) portfolios for the 500 largest stocks by market capitalisation, based on dispersion in analyst forecasts on the third Thursday of the previous month, and long the quintile with the lowest dispersion. The Market Risk Premium, Small Minus Big, High Minus Low and Up Minus Down factors are those calculated by Kenneth French. Betting Against Beta is the factor calculated by AQR Capital Management, LLC. Standard errors are adjusted for autocorrelation using the Newey-West method with a 12-month lag. The time period of data is from January 1983 to June 2018.

	(1)	(2)	(3)	(4)
VARIABLES	Dispersion Portfolio 1	Dispersion Portfolio 1 incl. BAB	Dispersion Portfolio 5	Dispersion Portfolio 5 incl. BAB
MRP	0.92***	0.92***	1.17***	1.17***
	(32.26)	(44.20)	(28.25)	(28.96)
SMB	-0.22***	-0.21***	0.37***	0.36***
	(-4.54)	(-5.98)	(4.06)	(4.64)
HML	0.07	-0.02	-0.04	0.03
	(1.07)	(-0.50)	(-0.57)	(0.30)
UMD	0.07*	0.02	-0.09*	-0.05
	(1.78)	(0.60)	(-1.74)	(-1.01)
BAB		0.17***		-0.13
		(3.92)		(-1.50)
Constant	0.15**	0.03	-0.24*	-0.15
	(2.08)	(0.50)	(-1.75)	(-0.93)
R-Squared	86.87%	88.71%	83.34%	83.83%
Observations	426	425	426	425

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1