Disagreement is Bad News

Bryan Lim*
Department of Finance
University of Melbourne

November 3, 2017

Abstract

I investigate whether the documented relationship between disagreement and future returns is driven by negative correlation between disagreement and fundamentals (unexpected earnings). I posit a model in which negative skewness in fundamentals interacts with heterogeneous weights in adopting new signals, generating higher disagreement when the underlying fundamentals are low. Across a number of empirical tests, I find robust evidence of the model's predictions. Conditioning on the realized fundamental, the ability for disagreement to predict future returns is virtually completely attenuated. Additionally, consistent with my model and inconsistent with prior hypotheses, I find the negative correlation between monthly analyst dispersion and next-month returns is driven by a combination of positive serial correlation in dispersion and negative correlation between returns and contemporaneous dispersion.

*e-mail: blim@unimelb.edu.au

Financial markets aggregate differential information across investors, and a key consideration in this process is the nature and the role of disagreement. What does it mean for investors to disagree, and how does that disagreement translate into prices? The literature has largely investigated two hypotheses. The first, as put forth by papers like Varian (1985) and David (2008), posits that disagreement generates risk for which investors must be compensated. According to this story, high disagreement pushes down prices and pushes up expected returns. Carlin, Longstaff, and Matoba (2014) examine the market for mortgage-backed securities and find results consistent with this hypothesis. The second hypothesis follows Miller (1977), who observed that when short selling is constrained, securities with higher disagreement should have higher prices, all else equal. Using the dispersion of analyst forecasts to measure disagreement in a given month, Diether, Malloy, and Scherbina (2002; henceforth DMS) examine whether returns in the subsequent month are lower for stocks with high disagreement relative to those with low disagreement. By the Miller logic, high disagreement should be correlated with abnormally high contemporaneous prices which cannot be arbitraged down due to constraints on short selling. Assuming high disagreement tends to dissipate, the price will tend to fall, so we should observe lower subsequent-month returns. Indeed, this is exactly what DMS find: high disagreement in month t is correlated with low returns in month $t+1$.

My paper revisits the relationship between disagreement and prices for equities and considers an alternate possibility: that disagreement predicts future fundamentals and the consequent returns in a way that is unrelated to the risk- or overpricing-based mechanisms. Where the existing has largely treated disagreement as exogenous, I hypothesize that it is instead an artifact of the unobserved financial state of the firm. According to my hypothesis, firms with poor (unannounced) fundamentals have higher pre-announcement disagreement. High disagreement consequently precedes low fundamentals, which in turn generate low returns.

In empirical tests across sixteen combinations of measures of disagreement, short-sale constraints, and fundamentals, where the fundamental of interest is quarterly earnings per share, I find compelling evidence that 1) disagreement predicts the unexpected and *unpriced* component in fundamentals; and 2) controlling for the realized fundamental, virtually all of the cross-sectional variation in future returns previously attributed to disagreement via a Miller-overpricing story disappears. Additionally, I find that when disagreement is measured by the monthly dispersion of analyst forecasts as in DMS, 3) increasing (decreasing) disagreement is matched by a contemporaneous decrease (increase) in the security's price; and 4) high (low) disagreement in months t and $t + 1$ is correlated with low (high) returns in month $t + 1$. While (3) is consistent with a risk-based story, (4) is not, since holding disagreement – i.e., risk – constant, the expected return should be positively correlated with the level of disagreement. Moreover, both (3) and (4) run counter to a Miller story. (3) and (4) underlie the ultimate dynamic: 5) disagreement is serially correlated, and the realized return for a given month is negatively correlated with the contemporaneous disagreement.

I frame the results with a stylized model which yields testable predictions regarding the dynamics between disagreement, returns, and fundamentals. The model is based on two building blocks. The first is agents' heterogenous weighting of new versus old information. The second is negative skewness in fundamentals, whereby positive fundamentals are more likely than negative fundamentals but are smaller in magnitude. When positive information arrives, it is relatively small in magnitude, so variation in agents' weights in updating their priors generates relatively small disagreement among them. When negative information arrives, it is relatively large in magnitude, so the equivalent variation in weights generates relatively large disagreement among them. If prices reflect mean beliefs, this skewness-based model predicts disagreement will be negatively correlated with the contemporaneous return as well as the future realized fundamental and the associated future return. Moreover, the correlation between disagreement and future returns will be driven only by disagreement's correlation with the fundamental. According to the model, conditioning on the fundamental, disagreement is uncorrelated with future returns.

The skewness model yields predictions which separately identify it from the Miller model. I take the two models' respective predictions to the data via two lines of inquiry. The first builds upon Berkman, Dimitrov, Jain, Koch, and Tice (2009; henceforth BDJKT), who apply the DMS analysis to earnings announcement returns. Under the assumption that an earnings announcement – i.e., the revelation of the information about which the disagreement exists – necessitates a reduction in disagreement, BDJKT examine the differential announcement returns for stocks with high versus low pre-announcement disagreement. Consistent with Miller, they find high-disagreement stocks have significantly lower announcement returns than low-disagreement stocks. With an expanded sample, I am able to replicate their results. Consistent with the skewness model, I additionally observe that high disagreement predicts low fundamentals and that conditional on the fundamental, disagreement has no additional predictive power over future returns. Crucially, these results hold across multiple specifications of disagreement, short-sale constraints, and fundamentals.

The second line of inquiry builds upon DMS. DMS test monthly returns versus prior dispersion, and I extend the tests to include contemporaneous dispersion. Extrapolation of a Miller overpricing mechanism to a dynamic setting predicts a negative correlation between changes in disagreement and the corresponding contemporaneous returns. Consistent with the skewness model and contrary to the overpricing model, I find that contemporaneous disagreement drives the return and that the observed predictability of returns from prior disagreement is due to serial correlation in disagreement.

Taken as a whole, my results can be distilled to a single basic conclusion: disagreement is bad news. The implications of this are manifold. First, they provide a novel mechanism by which disagreement predicts returns, alternative to the risk- and overpricing-based hypotheses. Disagreement is driven by fundamentals, which mechanically generate the observed future returns. Second, they raise questions for both behavioral-finance proponents and their market-efficiency counterparts. For the former, are the results driven by some sort of cognitive bias, and if so, why are they not arbitraged away? For the latter, is there a way to reconcile disagreement's predictive ability over the unpriced surprise in fundamentals within a rational framework? Finally, the results potentially speak to both the belief adjustment and, to a lesser extent, anchoring hypotheses in psychology.[1] Insofar as the mechanism in the skewness model describing the transformation of a public signal into beliefs is correct, the observed joint time-series dynamics of disagreement, returns, and fundamentals validates theories in which agents do not fully (rationally/optimally) update their priors when new information arrives.

My primary contribution is to the literature on disagreement and information diffusion. The innovation is the idea that observed disagreement is endogenously generated by underlying fundamentals. Prior research has typically treated disagreement as a state variable. Zhang (2006), for example, documents how information uncertainty (as measured by similar proxies as disagreement in my paper) contributes to market underreaction to public news, and Cen, Wei, and Yang (2016) observe that the interaction between disagreement and underreaction is informative about future returns. My results suggest that the unrealized fundamental is the state variable, and disagreement is determined by the state. Hong and Stein (1999) and Hong, Lim, and Stein (2000) connect momentum in returns to the diffusion of information across participants. The latter empirically tests a proposition in the former: that momentum strategies will be more effective on firms with lower analyst coverage, since analysts propagate information flow. For low-analyst-coverage stocks, bad news travels slower than good news, a result which the authors posit is driven by the asymmetric incentives for low-coverage firm managers to reveal good versus bad news. My skewness model overlaps with asymmetric-incentives theory advanced in Hong, Lim, and Stein (2000) and provides an explicit mechanism to tie news to disagreement. In the context of sell-side analysts, Scherbina (2008) observes that fewer forecasts are issued when the underlying state is bad, hypothesizing that career concerns incentivize analysts not to issue negative forecasts. Her insights build upon Hong, Lim, and Stein (2000), who argued that firm managers have asymmetric incentives to disseminate good versus bad news. I demonstrate a parallel channel connecting disagreement to firm funda-

[1]See Hogarth and Einhorn (1992) for belief adjustment and Kahneman and Tversky (1975) for anchoring.

mentals and returns, one that does applies to a broader set of market participants besides analysts. Crucially, my results hold for both analyst-based and market-based measures of firm fundamentals, suggesting that analyst career concerns alone do not drive the results.

My paper also contributes to the dispersion anomaly documented in DMS. Since its publication, several papers have investigated alternative explanations for the relationship between analyst dispersion and future returns. Johnson (2004) observes that expected returns for levered firms should decrease with idiosyncratic asset risk, so if disagreement proxies for idiosyncratic risk, it follows that high disagreement should be correlated with low future returns. Avramov, Chordia, Jostova, and Philipov (2009) demonstrate that dispersion is negatively correlated with credit ratings, and the differential returns between high and low analyst-dispersion firms is driven by differences in credit. My skewness model complements these papers by providing a mechanism connecting fundamentals to observed differences in analyst dispersion.

Finally, I contribute to the literature examining analyst bias and returns. Grinblatt, Jostova, and Philipov (2017) demonstrate that the ex-post bias in analyst forecasts is predictable, and for firms whose earnings are difficult to forecast, the predicted bias is negatively correlated with future returns. They posit that when earnings are difficult to forecast, market participants will rely more on analyst forecasts than when earnings are easier to forecast, and this "pied piper" effect leads to the observed correlation between difficulty of forecasting (e.g., high analyst dispersion) and future returns. Similarly, Veenman and Verwijmeren (forthcoming) argue that that analyst career incentives provide a channel through which the observed relationship between dispersion, ex-post bias, and returns can occur. The theory and results in my paper provide a complementary interpretation of these results, whereby the forecasts of analysts reflect the beliefs of the investor population at large. In this case, analyst bias is indicative of investor bias, a possibility supported by my finding that disagreement is correlated with both future ex-post bias and future standardized unexpected earnings, the latter an accounting measure which cannot be affected by analysts.

The structure of the paper is as follows. Section 1 presents a theoretical model, which is used to derive predictions that can be compared to those from Miller (1977). Section 2 details the construction of the data. In Section 3, I test the predictions using earnings announcements. In Section 4, I test the predictions using monthly analyst dispersion. Section 5 takes a deeper look at the disagreement measures. Section 6 concludes.

1 Theory and Predictions

In this section, I present a simple model connecting disagreement, fundamentals, and returns. The model is heavily stylized, abstracting from considerations like investor utility and markets clearing, in an attempt to convey the underlying mechanism as parsimoniously as possible. The model is purposefully limited in scope, having nothing to say, for example, about the plausibility of agents with common priors disagreeing, as Aumann (1976) described. What the model provides is a channel linking disagreement to both fundamentals and returns that is distinct from Miller (1977).

1.1 The Model

I model a market for a single security over three periods: $t \in \{0, 1, 2\}$. Analysts are trying to determine the value of the fundamental F, where F is realized at $t = 2$. I use the term "analysts" here to keep the description consistent with my main empirical tests, but fundamentally I am referring to all participants in the market. The distribution of F is given by:

$$F = \begin{cases} \Delta > 0 & \text{with probability } p > {}^{1}\!/_{2} \\ -K\Delta < 0 & \text{with probability } 1 - p \end{cases}$$

where $K > 1$ and $E[F] = 0$.

At time 0, the price of the security is P_0, and all analysts have the same belief about F: namely, that its expectation is 0.

At time 1, a public signal $S = F + \epsilon$ arrives, where ϵ is distributed with mean 0 and

$\sigma_\epsilon > 0$. Analyst n calculates her prediction x_n of F as a weighted average of her prior belief and S:

$$x_n = \lambda_n S + (1 - \lambda_n)0 = \lambda_n S$$

where $\lambda_n \in (0, 1)$, $\mu_\lambda < 1$, and $\sigma_\lambda \neq 0$. λ_n can be interpreted in multiple, non-mutually exclusive ways. One interpretation is that it represents the ability of the analyst to process the signal. High-ability analysts are able to process the signal faster than low-ability ones, meaning they have higher λ. Another interpretation is that it represents the weight the analyst places on new information when updating her priors. Lahiri and Sheng (2008) use λ to represent the weight attached to prior beliefs when signals are normally distributed. In the language of psychology, $1 - \lambda$ measures the analyst's *belief perseverance* (e.g., Anderson, Lepper, and Ross, 1980; Ross, Lepper, and Hubbard, 1975; Lord, Ross, and Lepper, 1979).

The condition that $\sigma_\lambda \neq 0$ means that there exists at least some variation across agents in their respective abilities. Imagining this as a repeated game, it is not necessarily the case that λ_n is fixed for analyst n in every market and every time period she participates. λ_n can be thought of specific to a particular analyst for a particular security over a particular period of time.

Analysts are atomistic and individually have no price impact. The time-1 price P_1 is the average expectation of the next-period price P_2:

$$P_1 = P_0 + \frac{\sum^N \lambda_n S}{N} = P_0 + \mu_\lambda S$$

Disagreement at time 1 is measured as the standard deviation of analysts' beliefs, which is equivalent to the the signal S times the cross-sectional variation in λ_n:

$$D_1 = \sigma(x_n) = S\sigma_\lambda$$

At time 2, F is revealed, and the price is $P_2 = P_0 + F$. Figure 1 illustrates the timeline.

[Figure 1 about here]

1.2 Predictions

Conditioning on F, I derive expectations for disagreement and returns. By "expectations", I mean the expected observed average, conditional on the ex-post realization of F. An equivalent interpretation is the expectation from the point of view of an omniscient but passive observer. I note that the analysts' expectations are not meaningful in this setting, since their behavior is constrained by the assumptions of the model. For example, in the cross-section of analysts, the average one-period expected return among them is 0 at both time 0 and 1.

The conditional expectation of disagreement at time 1 is

$$E[D_1|F] = E[\sigma(\lambda_n S)|F] = \sigma(\lambda_n(F+\epsilon)) = \sigma_\lambda |F| \quad (1)$$

assuming λ_n is uncorrelated with F and ϵ. The conditional expectations of the time-1 and 2 returns are, respectively,

$$E[R_1|F] = \frac{P_0 + \mu_\lambda F - P_0}{P_0} = \frac{\mu_\lambda F}{P_0} \quad (2)$$

$$E[R_2|F] = \frac{P_0 + F - (P_0 + \mu_\lambda F}{P_0 + \mu_\lambda F} = \frac{(1-\mu_\lambda)F}{P_0 + \mu_\lambda F} \quad (3)$$

Equations (1) to (3) tie disagreement and returns to realizations of F. Assuming that the distribution of λ_n is equivalent across securities (and independent of the realization of F), when F is positive we should observe low disagreement at time 1 and positive returns at times 1 and 2. When F is negative, we should observe relatively high disagreement at time 1 and negative returns at times 1 and 2.

We can flip these relationships around. Low disagreement should be correlated with positive contemporaneous returns and predict both positive future returns and fundamentals. Similarly, high disagreement should be correlated with negative contemporaneous returns and predict both negative future returns and fundamentals.

The disagreement result is given by Equation (1). Assuming the distribution of λ is independent of F, then if F is negatively skewed, negative fundamentals should manifest in higher disagreement. The return results – for time 2, in particular – are artifacts of the mean λ being less than 1.

The model predictions are easily applied to the empirical setting in BDJKT, wherein disagreement is measured just prior to an earnings announcement. To extend the model to the monthly setting in DMS, the model can be respecified as ending at period $T > 2$. From periods 1 to $T - 1$, the analyst updates her beliefs by placing weight λ_n on S and $1 - \lambda_n$ on her prior. As the current period t approaches T, her beliefs converge toward the fundamental:

$$x_{n,t} = \sum_{j=0}^{t-1} (1 - \lambda_n)^j \lambda S$$

Two predictions can be derived from this setting. First, conditional on a single signal S, disagreement is serially correlated. Second, since changes in the ranked level of disagreement can only occur with a new signal S, conditional on a change in ranked disagreement returns are negatively correlated with contemporaneous disagreement but not prior disagreement. To put this slightly differently: Controlling for serial correlation in disagreement, returns are negatively correlated with contemporaneous disagreement and uncorrelated with past disagreement.

1.3 Compared to Miller (1977)

The intuition in Miller (1977) has shaped the a considerable portion of the discussion on disagreement. Here I detail the predictions that come from a Miller-style model applied to the dynamic setting in the skewness-based model.

Miller models the market for a security as a downward-sloping demand curve interacting with an inelastic supply curve. The steepness of the demand curve indicates disagreement, and the x-intercept of the supply curve represents the degree to which short-sales are constrained. In contrast to the skewness model, Miller makes no reference to fundamentals. The implicit assumption in DMS and BDJKT is that dispersion is not correlated with fundamentals. Under this assumption, disagreement should predict future returns even conditional on the realized fundamental. According to this reading of Miller, amongst all stocks with (e.g.) high earnings surprises, those that had higher pre-announcement disagreement should experience lower returns.

Extracting dynamic predictions from Miller's static model requires making assumptions about how the supply and demand curves move. The assumptions I apply are consistent with those implicit in prior literature. In a Miller setting, changes in disagreement should manifest in changes in the slope of the demand curve. If:

1. Shifts in the supply curve are independent of changes to the demand curve, and

2. The point at which the demand curve pivots is both independent of the change in the slope (i.e., changes in disagreement are uncorrelated with shifts in the demand curve) and positioned to the right of the supply curve (i.e., the constraint is binding),

a number of straightforward predictions can be derived.

Figure 2 illustrates a Miller-style security market with two potential demand curves, one corresponding to high disagreement (D^H) and the other to low disagreement (D^L). When disagreement doesn't change from t to $t+1$, the demand curve remains in place, and the average contemporaneous return r_{t+1} should be 0. When disagreement increases ($D^L \rightarrow D^H$), the average return should be positive. When disagreement decreases ($D^L \rightarrow D^H$), the average return should be negative.

[Figure 2 about here]

Table 1 lists the corresponding predictions from my skewness model and Miller (1977), conditioning on some (potentially ex-post) observable. As noted previously, the expectation refers to the ex-post expected average. It does not refer to the ex-ante expectation of the participating analysts. As the empirical analyses will use ranked measures of variables rather than cardinal measures, in comparing the models' predictions for a cross-section of securities I'll henceforth abandon signs and magnitudes and instead use the relative terms "low" and "high". Accordingly, the "<0", "=0", and ">0" notations in Table 1 are to be read as "low", "average", and "high", respectively.

[Table 1 about here]

Panel A lists the predictions around earnings announcements. H1 states that conditional on high pre-announcement disagreement, the skewness model predicts low fundamentals, while Miller's model, by assumption, predicts average fundamentals (i.e., $F = 0$). H2 states that conditional on the realized fundamental, the skewness model predicts that the correlation between pre-announcement disagreement and the announcement return is 0. While this result is easily verified analytically (F is the only random variable), the intuition is that disagreement affects prices only through fundamentals, so conditional on the fundamental, cross-sectional variation in dispersion is uninformative about the announcement return. By contrast, Miller's model predicts the correlation between dispersion and is negative, regardless of the realized fundamental.

Panel B lists the predictions regarding monthly disagreement. In the skewness model, monthly disagreement is serially correlated (H3). Controlling for this serial correlation, what drives the return in a given month is the *contemporaneous* analyst dispersion, not the prior dispersion. the skewness model predicts high (low) dispersion is correlated with low (high) contemporaneous returns (H4/A/B and H5/A/B). Miller's model predicts that the change in dispersion is positively correlated with the contemporaneous return but has no prediction about the correlation between the level of dispersion and the contemporaneous return.

2 Data Construction

The data come from standard sources. I/B/E/S provides analyst EPS forecasts and monthly summaries. CRSP provides daily and monthly stock returns, prices, volumes, and shares outstanding, as well as index returns. I use Compustat for earnings and other corporate fundamentals. Institutional ownership is from Thomson Reuters 13f data. Markit provides indicative short-sale fees. For all variables except short-sale fees, the sample runs from 1985 to 2015. Tests involving short-sale fees are limited to a sample from 2002 to 2015.

In Section 3, I follow BDJKT and examine (-1, +1) buy-and-hold abnormal returns (BHAR) around quarterly earnings announcements. BHAR is calculated via a simple market-adjusted model using the CRSP value-weighted index.

I calculate multiple measures of disagreement, following BDJKT. The first is the dispersion of analyst forecasts (ANADISP). For stock i in quarter t, the sample of forecasts is the last EPS forecast for the quarter made by each analyst in the 45 days ending 2 days prior to the earnings announcement date. ANADISP is calculated as the standard deviation of analysts' forecasts for i in quarter t scaled by the mean forecast.[2] The second disagreement measure is return volatility (RETVOL), defined as the volatility of the stock return over 45 consecutive trading days, ending 10 days prior to the earnings announcement. The third is share turnover (TURN), defined as average daily ratio of traded volume to shares outstanding over the same 45-day window as RETVOL. The fourth is income volatility (INCVOL), defined as standard deviation of the seasonally-adjusted quarterly operating income before depreciation divided by total assets over the prior 20 quarters.

I calculate two measures of short-sale constraints. The first is the indicative fee – generally the rebate rate – reported by Markit for stock i on the most recent date at least 10 days prior to the earnings announcement. The second measure is the estimated retail ownership (RETAIL) of the stock, defined as one minus the percentage held by institutions. The latter is the sum of shares held by institutions (according to 13f filings) at the end of the quarter scaled by the shares outstanding.[3]

[2] I have also calculated this measure scaling by the stock price. The results are not qualitatively different.

[3] In the terminology of BDJKT, RETAIL is simply one minus their institutional ownership measure, INSOWN. I have used RETAIL to maintain consistency with my first short-sale constraint measure, the indicative fee (FEE), such that high RETAIL/FEE indicates high constraints.

In addition to the dispersion and short-sale constraint variables, I add two measures of fundamentals. The first, earnings surprise (ESURP), is the difference between the announced EPS and the mean forecast from the 45-day window used to calculate ANADISP, scaled by the standard deviation of the forecasts.[4] The second measure of fundamentals, standardized unexpected earnings (SUE), follows Bernard and Thomas (1989) and is calculated as

$$SUE_t = \left\{ \begin{array}{ll} (UE_t - \overline{UE}_{(t-20,t-1)})/\sigma(UE_{(t-20,t-1)}) & \text{if } N \geq 20 \\ (UE_t - \overline{UE}_{(t-N,t-1)})/\sigma(UE_{(t-N,t-1)}) & \text{if } 10 \leq N < 20 \end{array} \right\}$$

where

$$\begin{aligned} UE_t &= EPS_t - EPS_{t-4} \\ \overline{UE}_{(t-N,t-1)} &= \text{Average } UE_t \text{ from } t-N \text{ to } t-1 \\ \sigma(UE_{(t-N,t-1)}) &= \text{Standard deviation of } UE_t \text{ from } t-N \text{ to } t-1 \\ N &= \text{Number of available quarterly observations prior to } t \end{aligned}$$

Both ESURP and SUE qualitatively match the stylized distribution of F in the skewness model. Recall that F is assumed to be negatively skewed with mean 0. The skewness drives the differential disagreement when the fundamental is high relative to when it is low. In my sample, both earnings surprises (ESURP) and standardized unexpected earnings (SUE) demonstrate significant negative cross-sectional skewness. In the overall sample, ESURP and SUE have skewnesses of -0.526 and -0.992, respectively. The average quarterly cross-sectional skewnesses for ESURP and SUE are -0.548 and -0.881 respectively, with both being significantly different from 0 at the 1% level.

The multiple measures of disagreement, short-sale constraints, and fundamentals yield

[4]The construction of ESURP may be problematic, as its denominator is equivalent to the numerator of ANADISP, implying a potentially mechanical inverse relation to ANADISP. I stress "potentially" since the numerator of ESURP can be positive or negative. In unreported results, respecifying the denominator of ESURP as the share price does not qualitatively change the results.

a large number of possible combinations ($4 \times 2 \times 2$) to analyze. In each test, the baseline results use analyst dispersion, the indicative short-sale fee, and earnings surprises, under the presupposition that these best represent the parameters in the theoretical models discussed in Section 1. I then report results for all the remaining combinations. The aggregate results prove to be largely consistent with each other. This robustness suggests that the results are not driven by things specific to the disagreement measure, like analyst career concerns (e.g., analysts may have incentives not to report their true beliefs), or by sample selection (e.g., the intersection of firms with both analyst coverage and short-sale fees reported in Markit).

For the monthly analysis, I follow DMS and use the I/B/E/S monthly summary file for quarterly EPS forecasts, where ANADISP is again measured by the standard deviation of analyst forecasts scaled by the mean forecast. Excess returns are calculated as the monthly raw return less the CRSP value-weighted index over the same month.

3 Earnings Announcements

The key finding in DMS is that high analyst dispersion in month t predicts low returns at $t+1$, which they primarily explain this result via Miller (1977): High dispersion pushes up the price at t, necessitating lower returns at $t+1$. BDJKT suggest a more rigorous test of Miller involves the resolution of uncertainty such that the prior dispersion decreases. They use earnings announcements as such a resolution, their rationale being that once earnings are announced, there is less for agents to disagree upon.

In this section, I revisit BDJKT's key tests on announcement returns and add parallel tests for the realized fundamentals. The latter is to investigate the possibilities that 1) disagreement predicts fundamentals and 2) the return results are at least partially driven by fundamentals. I then run multivariate regressions conditioning on the realized fundamental to determine whether disagreement has any additional explanatory power for future returns.

3.1 Single-Sorted Portfolios

BDJKT's first tests involve sorting firms into quintiles by their pre-announcement disagreement at the end of each quarter and averaging the subsequent earnings announcement buy-and-hold abnormal return (BHAR) for each firm in the quintile. If the Miller intuition is correct, high-disagreement firms should experience low BHARs.

Indeed, both BDJKT's and my results confirm this. In Table 2, the first row of Panel A lists average BHAR for firms sorted into quintiles based on their pre-announcement analyst dispersion (ANADISP). The average BHAR across dispersion quintiles largely follows the Miller-based prediction, increasing moderately from the first to second quintiles, then decreasing monotonically thereafter. More relevantly, the difference in BHAR between the lowest and highest quintiles is positive and statistically significant.

[Table 2 about here]

The second row lists the realized earnings surprise (ESURP) for firms in each quintile. Remarkably, the pattern in earnings surprises is virtually identical to that in announcement returns. ESURP is monotonically decreasing, with the difference between the lowest and highest quintiles being positive and significant. This result lines up with the skewness model's H1 prediction, which states that the level of dispersion negatively predicts the realized fundamental.

The result in the top two rows of Panel A in Table 2 represents the empirical starting point for this paper. Abstracting from the legitimate concern about whether ESURP is a reliable measure of the market-wide surprise in the earnings announcement, the parallel trends in BHAR and ESURP across disagreement open up the possibility that the observed relationship between disagreement and future returns is driven at least in part by a correlation between disagreement and the surprise in fundamentals. If this results is generalizable beyond analyst dispersion and earnings suprise, it would not just be the case that disagreement predicts returns. Disagreement would also predics the unpriced bias in analysts' forecasts. This is consistent with the skewness model's prediction H1 in Table 1, but even if the skewness model is not correctly specified, the empirical result is striking in its potential challenge to how we think of information flows and prices in ostensibly efficient markets.

Having said that, ESURP may not be an appropriate proxy for the true (market) surprise in fundamentals. A voluminous literature has analyzed the incentives of analysts to report truthfully or accurately. For example, analysts have empirically been found to be systematically optimistic, as in DeBondt and Thaler (1990) and Dreman and Berry (1995). Trueman (1994) and Welch (2000) document that analysts tend to herd in their recommendations. Theoretical models like Scharfstein and Stein (1990) and Lim (2001) suggest that career concerns may shape analysts forecasts, and empirical papers like Michaely and Womack (1999), Dechow, Hutton, and Sloan (1998), and Hong and Kubik (2003) provide supportive evidence. Given these concerns, using a measure (ESURP) based on what may be biased forecasts may not necessarily proxy for the true surprise in earnings announcement. One may be similarly concerned that using analyst dispersion as the measure of disagreement is confounded by analysts' biases.

To address these concerns, I rerun the univariate tests involving quintile sorts using the other 7 combinations of disagreement and fundamentals detailed in Section 2. The results fill out the remainder of Table 2. Each pair of rows corresponds to a disagreement-fundamental measures pair.

The second two rows of Panel A keep ANADISP as the disagreement measure but use standardized unexpected earnings (SUE), an accounting measure, as the measure of fundamentals. This change to the fundamentals alters the sample, as the set of observations with both ANADISP and ESURP is not identical to the set with both ANADISP and SUE. By design, I do not restrict the samples to be identical for all disagreement and fundamentals (and, later, short-sale constraint) combinations, so as to reduce the possibility that the results are driven by sample selection issues. In this case, changing the fundamentals to SUE does not qualitatively affect the results. SUE is monotonically decreasing while BHAR is again nearly monotonically decreasing as one moves across

ANADISP quintiles. The positive and significant difference in BHAR across the lowest and highest quintiles is matched by a positive and significant difference in SUE across the two quintiles.

Using analyst forecasts to measure disagreement is potentially problematic if analysts have incentives to not report truthful forecasts. To attenuate this concern, I follow BDJKT's alternate measures of disagreement.

The prior stock return volatility (RETVOL) is a market-based measure of disagreement and therefore less subject to the distortions that potentially affect analyst forecasts. In Panel B, while the mean BHARs are not monotonically decreasing across RETVOL quintiles, the *Low* - *High* estimates are positive and significant. The mean fundamentals are monotonically decreasing, and the *Low* - *High* estimates match the BHAR results in sign and significance.

Share turnover (TURN), defined as the percentage of shares traded daily, is another market-based measure of disagreement. The results in the first two rows of Panel C are are decidedly inconsistent with the skewness model. While the *Low* - *High* BHAR is positive and significant, the corresponding differential ESURP is *negative* and significant. Looking at the individual quintile averages, this result is even more puzzling. BHAR is roughly flat across the first four TURN quintiles, then drops in the top quintile. Conversely, ESURP is increasing as one moves across TURN quintiles. In and of itself, that ESURP is increasing with TURN might be reconciled with a story about turnover increasing when good news is to be revealed in fundamentals. But the corresponding low BHAR suggests that the pre-announcement price was somehow too high relative to the realized (good) fundamental. This outcome is not easily explained by a skewness-, overpricing-, or risk-based model. When using SUE as the measure of fundamentals, I again observe that fundamentals are declining with disagreement and that the differences in *Low* - *High* BHAR and *Low* - *High* fundamentals line up with the baseline results.

Finally, income volatility (INCVOL) is used as an accounting-based measure of disagreement. As reported in Panel D, the INCVOL results are mixed. In the ESURP and the SUE samples, neither the average BHAR nor average fundamental is monotonically declining across INCVOL quintiles. In the first two rows, both the average BHAR and ESURP are inverted-U shaped, with the *Low - High* mean BHAR and ESURP estimates positive and significant. Using SUE as measure of fundamentals, the positive and significant *Low - High* difference in BHAR is paired with a corresponding *negative* and significant difference in SUE. A confounding factor here is that INCVOL and SUE are mechanically inversely related. The numerator of INCVOL is the prior volatility of seasonally-adjusted operating income, while the denominator of SUE is the prior volatility of seasonally-adjusted earnings. The average SUE in the sample is negative, so if the SUE denominator is mechanically high for the high INCVOL group, the measured SUE will be pushed toward 0 (and potentially above the SUE of the low INCVOL group). Should this be the case, the INCVOL/SUE test is improperly specified.

Overall, the whole of Table 2 is largely directly supportive of the skewness model's H1 prediction and inferentially supportive of its H2 prediction. 6 of the 8 (or 7, depending on the validity of the INCVOL/SUE combination) tests are consistent with the skewness model's H1 prediction that high disagreement predicts low fundamentals. Moreover, in these 6 tests, the positive and significant difference in *Low - High* BHAR is matched by an equivalent result for the fundamental, supportive of the H2 prediction.

3.2 Double-Sorted Portfolios

The next set of tests in BDJKT double-sort firms into nine groups. Each quarter, firms are assigned to Low (bottom 30%), Medium (middle 40%), and High (top 30%) groups based on their ranked short-sale constraints. Within each of these groups, firms are sorted into Low, Medium, and High groups based on their ranked disagreement. For a given short-sale constraint group, if the Miller intuition is correct we should observe announcement returns to be decreasing as disagreement increases. In the skewness model, there are no short-sale restrictions, so there is limited inference to be made about returns or fundamentals across varying levels of short-sale constraints. Holding fixed the level of short-sale constraints, the intuition of the skewness model still applies.

Panel A of Table 3 lists the average earnings announcement BHAR for each of the nine portfolios. The results are consistent with the equivalent tables in BDJKT, in that 1) within a given short-sale constraint (the indicative fee in the present case versus institutional ownership in BDJKT) group, the average BHAR is decreasing in pre-announcement analyst dispersion and 2) within each analyst dispersion group, the average BHAR is decreasing in the level of the short-sale constraint.

[Table 3 about here]

Further examination of Panel A provides evidence both for and against Miller's (1977) hypothesis. On the one hand, conditioning on the short-sale constraint, higher disagreement is associated with lower announcement returns, and conditioning on disagreement, more binding short-sale constraints are associated with lower returns. These results align with the Miller story. On the other hand, the positive and significant difference in announcement returns between the *Low* and *High* disagreement groups for the *Low* fee group – the group that should be easily shorted – suggests that limits to arbitrage may not be driving the return result.

In Panel B of Table 3, I calculate the average earnings surprise ESURP for each group and document a comparable pattern for ESURP as for BHAR. Across a given short-sale fee group, ESURP is decreasing with analyst dispersion. Within a given analyst dispersion group, ESURP is decreasing with the short-sale fee. The results in Panel B are striking in their ability to match the variation returns across the short-sale fee/analyst dispersion groups.

In the context of the skewness model, absent significant differences in BHAR between the *Low* and *High* short-sale constraint groups, conditioning on the disagreement group to determine whether short-sale constraints are correlated with fundamentals is not informative. The skewness model has no prediction about what the difference in fundamentals between *Low* and *High* short-sale constraint firms should be. Moreover, the order of the sorting creates an empirical problem, one that can be conveyed with a representative example. The analyst dispersion for the *High* FEE, *Low* ANADISP group may be very different from the dispersion for the *Low* FEE, *Low* ANADISP group. Were it the case that the differential BHAR within the *Low* disagreement group was not significant, the positive and significant differential fundamentals would not shed light on the predictions of the skewness model.

As before, the baseline analysis is subject to the possibility that the chosen measures of disagreement, fundamentals, and short-sale constraints are inappropriate for testing Miller's (1977) and the skewness models. I rerun the tests across the remaining 15 combinations of disagreement, fundamentals, and short-sale constraints. For each of these triples, I report the *Low* - *High* BHAR and the *Low* - *High* fundamental averages, both within short-sale constraint groups and within disagreement groups.

Table 4 details the key results from applying the tests in Table 3 to every combination of disagreement, fundamentals, and short-sale constraints. The first three columns report the differences in average BHAR and average fundamentals between the *Low* and *High* disagreement (DA) group, conditional on the short-sale constraint (SSC) group. The second three columns report the differences between the *Low* and *High* short-sale constraint group, conditional on the disagreement group. The table is split into four panels, one for each measure of disagreement. Each panel is then split into two sets based on the short-sale constraint used: the indicative fee (FEE) or the percentage of shares outstanding not held by institutional investors (RETAIL). Each of those sets is then further split by the measure of fundamentals. For reference, the top two rows of Panel A correspond to the *Low* - *High* test statistics from Table 3. Each pair of subsequent rows represents the equivalent statistics from running the same test procedure but with different combinations of the disagreement, fundamental, and short-sale constraint measures.

[Table 4 about here]

Before unpacking Table 4, I'll list what it is we might hope to learn from it:

1. Replicate BDJKT's results, not only for the multiple measures of disagreement but also for the multiple measures of short-sale constraints. By "replicate", I'm specifically referring to the majority of positive and significant differences in average BHAR between the *Low* and *High* disagreement (short-sale constraint) groups within a given short-sale constraint (disagreement) group.

2. Determine whether disagreement is correlated with fundamentals conditional on the short-sale constraint. Though the skewness model makes no reference to short-sale constraints, its predictions should hold if we fix the level of the constraint: increasing disagreement should predict lower fundamentals.

   (The reverse test – whether disagreement is correlated with the short-sale constraint conditional on the disagreement group – is not relevant, for the reason detailed in the earlier discussion of Table 3.)

3. The final and ultimate goal is to observe whether the results for *Low* - *High* earnings announcement BHARs within short-sale constraint groups and within disagreement groups are matched by similar results for *Low* - *High* realized fundamentals within those same groups. Confirmation of such a pattern, as found in Table 3, would be consistent with the skewness model, which predicts the announcement returns observed in BDJKT are driven by fundamentals and not disagreement itself.

With these considerations in mind, I have shaded cells in Table 4 in which 1) within a short-sale constraint group, the difference in either BHAR or the fundamental is negative and significant; or 2) within a disagreement group, the differential fundamental is not positive and significant when the corresponding difference in BHAR is. The purpose of the shading is to identify the results which run strongly counter to either the skewness model's or Miller's predictions.

Some general patterns are observed across the four disagreement measures. Within SSC groups, the differential BHAR is generally positive and significant, supporting both Miller's and my story. The cases in which the differential BHAR is not significant may still be consistent with Miller, in that they generally occur for the *Low* and *Medium* SSC groups, which by definition should be less affected by limits to arbitrage. Within SSC groups, the majority of differential fundamentals are positive and significant, consistent with the skewness model's H1 prediction. The cases in which they are not positive echo the cases from Table 2 (TURN/ESURP and INCVOL/SUE).

Within disagreement groups – i.e., the last three columns of Table 4 – the overwhelming majority of differential BHARs are positive and significant, and these results are matched by positive and significant differential fundamentals. This suggests that the portion of the observed BHAR attributed to the interaction of disagreement and short-sale constraints in prior literature may be at least partially explained by the realized fundamentals.

Working through the different disagreement measures one at a time, Panel A lists results when disagreement is measured by analyst dispersion. The results are strongly supportive of the skewness model's central prediction that disagreement proxies for fundamentals. While the BHAR results are consistent with the Miller interpretation, the ESURP and SUE results suggest that the observed announcement return is driven at least partially by the realized fundamental. In virtually every case where the differential BHAR is positive and significant, the realized fundamental is as well.

In Panel B, return volatility measures disagreement. Within SSC groups, the results for differential BHAR here are comparatively less supportive of either the Miller or the skewness model than they were Panel A. Specifically, one case (SSC = FEE, fundamental = ESURP) generates negative and significant differential BHARs, implying that high disagreement resulted in higher announcement returns. The results for fundamentals are nevertheless strongly supportive of the skewness model's prediction regarding their relationship with disagreement. The average *Low - High* fundamentals are positive and significant within each SSC group.

The disagreement measure in Panel C is share turnover. Echoing the results from Table 2, the sign on the differential ESURP within SSC groups is negative in 5 of the 6 tests. Within TURN groups, the patterns in differential BHAR (i.e., positive and significant) are matched in the patterns in differential fundamentals.

Panel D lists results when the disagreement measure is income volatility. Again, the results here echo those from Table 2. Specifically, within short-sale constraint groups, the differential SUE is negative and significant, but again, the caveat regarding a potentially mechanical inverse relationship between INCVOL and SUE applies here. The within-SSC-group results based on ESURP are largely consistent with the skewness model, in that in 5 of the 6 tests, the sign and significance of the differential BHARs is matched by those of the differential ESURPs.

Overall, the within-SSC-group results from Table 4 largely confirm those from the single sorts in Table 2, that the observed difference in BHAR between low and high disagreement stocks is generally accompanied by a corresponding difference in the realized fundamental. The within-DA-group results further suggest that the observed differential BHARs are driven in part by differential realized fundamentals.

3.3 Multivariate Analysis

The results in Sections 3.1 and 3.2 provide direct support for the skewness model's H1, that disagreement predicts the realized fundamental, but only inferential support for the skewness model's H2, that conditional on the fundamental, disagreement does not predict announcement returns. To test H2, I construct a variation of the earnings response models used in the accounting literature[5].

Each quarter t, I sort firm i into quintile q based on its realized fundamental. Then, for each q, I run Fama-MacBeth regressions on the following model:

$$BHAR_{it} = \alpha_q + \beta_{1q} DA_{it} + \beta_{2q} SSC_{it} + \beta_{3q} DA_{it} \times SSC_{it} \quad (4)$$

where $BHAR_{it}$ is i's earnings announcement BHAR at t; DA_{it} is i's pre-announcement disagreement; SSC_{it} is its pre-announcement level of the short-sale constraint; and $DA_{it} \times$

[5]See, for example, Collins and Kothari (1989).

SSC_{it} is the interaction of disagreement and the short-sale constraint. Casually observed, Equation (4) appears to be an earnings response model without earnings. Rather, it's an earnings response model in which the earnings response coefficient times the average of the measure of earnings is represented by the intercept α_q for each q.

With regards to Miller's and the skewness model's respective H2's, the predictions for the coefficients in Equation (4) are clear. According to the Miller model, having conditioned on the realized fundamental, the coefficient on $DA \times SSC$ – and, depending on one's interpretation of Miller, on DA – should be negative. By contrast, according to the skewness model, having conditioned on the realized fundamental F, the coefficients on DA and $DA \times SSC$ should be zero. Failing that, a supportive if not confirming result would be for the coefficients to be negative for the lower realized fundamental quintiles and positive for the higher realized fundamental quintiles. This result would be obtained if the mean of λ were negatively correlated with the magnitude of F. That is, if high absolute F was tied to low μ_λ, then the pre-announcement price would be relatively closer to the pre-signal price, implying the announcement return would be greater in magnitude than it would be if μ_λ were uncorrelated with disagreement.

Table 5 presents results from the baseline ANADISP/FEE/ESURP combination. Each column represents observations in which a firm was in the qth quintile in ESURP for a given quarter. ANADISP and FEE are the winsorized raw (unranked) measures of analyst dispersion and indicative fees.

[Table 5 about here]

Looking at the results, the constant terms line up as one would expect, increasing monotonically with the earnings surprise quintile. More importantly, the results for ANADISP and ANADISP×FEE are largely consistent with my H2 and entirely inconsistent with the corresponding Miller prediction. Conditioning on the realized fundamental, neither analyst dispersion nor its interaction with the short-sale fee has a negative and significant statistical correlation with the announcement return. Even if the mechanism in the skewness model is not correct, what is clear from Table 5 is that the Miller mechanism is not driving the majority of the cross-sectional variation in BHAR. In two of the ten cases, the coefficient is positive and significant, suggesting that higher dispersion leads to higher returns even after conditioning for the realized fundamental. Moreover, if one were to relax the assumption applied to Miller that disagreement is not correlated with the fundamental and argue that limits to arbitrage drive the pre-announcement price up, we should observe in the coefficients for ANADISP, FEE and ANADISP×FEE all being negative for the lower quintiles, but this is not borne out in the results.

Table 6 tabulates results from estimating Equation (4) for each quintile based on the remaining 15 combinations of disagreement, short-sale constraints, and fundamentals. To keep the table size manageable, I report only the coefficients on the disagreement measure (DA) and its interaction with the short-sale constraint measure (DA×SSC). With regard to the omitted coefficients:

1. As one might expect, the constant term is increasing monotonically with the fundamentals quintile in nearly every specification. In the instances where this is not the case, the constant term is not significant.

2. For no combination is there a pattern in the short-sale constraint coefficients that is consistent with a Miller story. There are sporadic instances of one or (rarely) two SSC coefficients being negative and significant, but there are a similar number of instances where the coefficient is positive and significant. The sum of the SSC results weigh strongly against a Miller interpretation.

[Table 6 about here]

As before, the table has four panels, one for each disagreement measure. Before discussing the individual results, I'll summarize the cumulative takeaway: For no combination of disagreement, short-sale constraints, and fundamentals are the coefficients on DA×SSC uniformly negative across all quintiles. The Miller story implies that the coefficient on DA×SSC should be negative and significant, yet, as seen by the five shaded cells in Table 6, this is true in only a small minority of the test cases. There are sporadic instances in which either the coefficient on DA or DA×SSC is negative and significant, but the vast majority of the estimated coefficients are either insignificant or occasionally positive and significant.

Working through the individual results, Panel A lists the results using ANADISP as the measure of disagreement. The results here overwhelmingly support the skewness model over Miller's. There is only one instance in which the coefficient on DA is negative and significant (Quintile 1, RETAIL/SUE) and no instance in which DA×SSC is negative and significant. The results strongly support the hypothesis that disagreement drives returns only through their correlation with future realized fundamentals.

In Panel B, I report results using RETVOL to measure disagreement. As opposed to the ANADISP-based estimates, the coefficients on RETVOL are significant in a large number of cases, though the relative ordering of these coefficients across quintiles is potentially more suggestive of the skewness model than Miller's. Take, for instance, the results for the FEE/ESURP combination in the first two rows of the panel. The coefficients on DA are negative for the *Low* fundamental quintile and then monotonically increasing as we move across quintiles. This is consistent with the scenario I detailed earlier, in which the magnitude of $|F|$ is correlated with the mean of λ. But this interpretation requires a fairly generous reading of the model. The most accurate reading of the monotonically increasing point estimates is that they support neither the Miller nor skewness model.

The results when TURN measures disagreement are reported in Panel C. While there are five cases in which the coefficient on DA is negative and significant and four cases in which the coefficient on DA×SSC is negative and significant, overall the TURN results strongly support the skewness model over Miller's.

Finally, Panel D lists results when INCVOL is the measure of disagreement. Again, despite the occasional negative and significant coefficient on either DA or DA×SSC (as well as a positive and significant coefficient, twice), the INCVOL results strongly support the skewness model over Miller's.

The lack of negative and significant coefficient estimates for DA×SSC works strongly against a Miller interpretation and for the skewness model's predictions. Given that I control for SSC and its interaction with DA, the instances of negative and significant coefficients for DA are not necessarily supportive of Miller. That they are predominantly confined to the lower fundamental quintiles and that they are in some cases matched by positive and significant coefficients for the higher fundamental quintiles can be reconciled in the skewness model if one allows for the mean of the weights (μ_λ) to be negatively correlated with the magnitude of the fundamental ($|F|$).

Taken together, the single-sorted, double-sorted, and multivariate results in this section provide support of the skewness model's two predictions (H1 and H2) regarding fundamentals. In the majority of test specifications, disagreement is correlated with future fundamentals, and the realization of the fundamental and not disagreement itself drives the realized earnings announcement return.

4 Monthly Returns

In this section, I revisit the monthly dispersion-return relationship documented in DMS. The innovation is to frame the analysis in terms of changes in dispersion, truer in some sense to the original Miller proposition. The section is intended to test the respective H3 through H5 predictions listed in Panel B of Table 1.

According to the skewness model, high disagreement at t should correspond to low contemporaneous returns R_t (H4); high disagreement at t and $t+1$ should correspond to high $t+1$ returns R_{t+1} (H4A); and high disagreement at t and low disagreement at $t+1$ should correspond to low $t+1$ returns (H4B). H5, H5A, and H5B are the corresponding opposite predictions for low disagreement at t. The predictions can be summarized compactly: Returns at t is negatively correlated with the contemporaneous disagreement. This contrasts with the Miller predictions, which are no prediction for R_t conditional on D_t; zero (excess) return when D_t and D_{t+1} are both high or both low; and high (low) R_{t+1} when D_t is low (high) and D_{t+1} is high (low).

In my first tests, each month I sort firms into quintiles based on their monthly analyst dispersion, as measured using the monthly summary measures from I/B/E/S. I create 25 unequal portfolios based on firms' t and $t+1$ dispersion quintiles, then report the mean $t+1$ monthly portfolio excess return, measured as the raw return minus the CRSP value-weighted index for the month. Results are presented in Table 7. To read the table, (e.g.) the cell corresponding to $\text{ANADISP}_t = 1$ and $\text{ANADISP}_{t+1} = 3$ reports the average next-month excess return for firms which were in the lowest (1) analyst dispersion quintile in the current month and in the middle (3) quintile in the next month.

[Table 7 about here]

DMS's key observation is the final column of Table 7, which shows next-month returns clearly declining with dispersion. What's unclear in their analysis is what the null hypothesis should be regarding the time-series of dispersion. Should dispersion be mean reverting (*median* reverting, more precisely), in which case firms on average move in and out of the middle quintile? If so, the Miller logic implies that high-dispersion stocks should experience low future returns, and low-dispersion stocks should experience high future returns, assuming movements in short-sales constraints aren't correlated with dispersion. This would seem to fit the results in the final column.

Alternatively, should dispersion be serially correlated? In this case, the Miller model would predict (as in H4 and H5) average returns for firms whose dispersion didn't change; high returns for firms whose dispersion increased; and low returns for firms who dispersion decreased. The two-way results in Table 7 do not support these predictions and instead imply that the next-month returns are driven by serial correlation in disagreement, consistent with the $T > 2$ extension of the skewness model. Fixing the month t dispersion (i.e., moving across a given row), the average $t+1$ excess returns are decreasing with the $t+1$ dispersion, exactly what my extended model predicts and exactly the opposite of what the Miller model predicts. What the final column – and what DMS – is picking up is predominantly the diagonal of the matrix. Dispersion at t is correlated with dispersion at $t + 1$, and if dispersion at $t + 1$ drives the contemporaneous return, it will appear as though dispersion at t predicts future returns.

A potential concern with this analysis is that one third of the observations overlap with earnings announcements, potentially confounding the results. In unreported results, I rerun the tests, first including only firm-months without a quarterly earnings announcement and second including only firm-months with a quarterly earnings announcement. The results are not qualitatively different in either subsample.

My next tests build on the underlying dynamics revealed in Table 7. For each firm-month, I calculate the change in dispersion quintile from the prior to the current month. I then calculate the average monthly excess return for all stocks with a given change in quintiles. Table 8 displays the average excess return based on the change in quintiles, as well as the number of observations with that change. Two results can be seen:

1. Dispersion is not mean/median-reverting but rather serially correlated. The majority of observations are clustered at 0: no change in the ranked dispersion from one month to the next. 90% of the observations are clustered between -1 and +1.

2. Excess returns are negatively related to changes in dispersion, consistent with the skewness model and inconsistent with Miller's.

[Table 8 about here]

To identify the extent to which returns are driven by correlation with contemporaneous dispersion as opposed to correlation with the change in dispersion, I run two sets of Fama-MacBeth regressions where the $t + 1$ excess return is the dependent variable. Unlike earlier tests, here I use the actual dispersion measure, not the quintile rank. In the first specification, the explanatory variable is ΔANADISP, the (1%, 99%) winsorized raw change in analyst dispersion from month t to $t + 1$. Column 1 of Table 9 reports a negative and significant coefficient on the change in analyst dispersion, inconsistent with Miller and consistent with the skewness model. In the second specification, I add the explanatory variable ANADISP_{t+1}, the winsorized analyst dispersion at $t + 1$. In Column 2, again consistent with the skewness model's predictions and inconsistent with their Miller counterparts, I find the coefficient on ANADISP_{t+1} is negative and significant, with the coefficient on ΔANADISP no longer being statistically significant.

[Table 9 about here]

In sum, the results indicate that 1) returns are negatively correlated with the contemporaneous level of disagreement and 2) the predictive relationship between disagreement and future returns is driven by serial correlation in disagreement. The Miller mechanism finds little support in the results, as does a risk-based hypothesis, which predicts high returns when dispersion is high for consecutive periods. That returns are not driven by prior disagreement but rather current disagreement is consistent with my extended model in which changes in disagreement correspond to new information about the fundamental.

5 Analyzing Disagreement

Excluding income volatility INCVOL, the remaining three disagreement measures used in Section 3 reflect the actions of market participants – analysts and investors – over 45-day windows. In this section, I calculate characteristics of these three disagreement measures over their estimation windows to shed additional light on the dynamics underlying the preceding results. In Table 10, I present averages for the calculated characteristics, sorted by the dispersion quintile. The purpose here is exploratory, so I do not run formal tests other than simple difference-in-means t-tests. I do not run t-tests on the individual averages, since for many of the variables it is not clear what the appropriate null-hypothesis values should be.

5.1 Analyst Dispersion

For the sample underlying each analyst dispersion (ANADISP) observation, I calculate NUMANALYSTS, the number of unique analysts issuing forecasts. Hong, Lim, and Stein (2000) argue that the number of analysts covering a firm proxies for the speed at which negative information about that firm diffuses. The first row of Panel A in Table 10 indicates that high analyst dispersion is correlated with lower analysts covering the firm, with the difference in average analyst coverage between the lowest and highest quintiles positive and statistically significant, suggesting the possibility that part of the mechanism driving higher disagreement is lower analyst coverage.

[Table 10 about here]

LOWLATE is calculated as the proportion of the forecasts below the median ("low") in the estimation window which were submitted after the median announcement date ("late"). LOWLATE conveys whether the lower forecasts in the estimation window tended to occur early or late relative to higher forecasts. LOWLATE being positively correlated with analyst dispersion is consistent with the theory advanced in Hong, Lim, and Stein (2000), where good and bad information diffuse asymmetrically, if analysts are heterogeneous in their speed of adopting a common signal. This is exactly what is observed in the second row of Panel A: LOWLATE is increasing with analyst dispersion.

SKEW(FC) is the skewness of the analysts' (final) forecasts. The motivating question is whether high disagreement tends to be caused by asymmetric outliers. The third row of Panel A indicates that the skewness of forecasts is on average increasing with analyst dispersion. In particular, high analyst dispersion stocks have positively skewed forecasts. The skewness neither supports nor falsifies the skewness model but rather gives some indication of what the distribution of λ_n might be.

Finally, I calculate BELOWMEDIAN as the proportion of forecasts which were below the trailing five-forecast[6] median at the time they were announced. BELOWMEDIAN

[6] The trailing five-forecast window includes forecasts which were not used to calculate ANADISP.

indicates whether forecasts were predominantly negative relative to those issued immediately prior. In the fourth row of Panel A, I document average BELOWMEDIAN is increasing with analyst dispersion, suggesting that high dispersion is on average driven by relatively negative forecasts.

5.2 Return Volatility

For each 45-day return volatility (RETVOL) estimation window, I calculate CUMEEXRET as the cumulative buy-and-hold return of the stock less the corresponding buy-and-hold return on the CRSP Value-Weighted index. If the skewness model is correct and returns trend toward the yet unrealized fundamental, CUMEEXRET should be lower for high RETVOL observations. The first row of Panel B in Table 10 indicates the opposite: The highest RETVOL observations have significantly higher CUMEEXRET than the lowest RETVOL observations.

The second row of Panel B documents NEGEXRET, the proportion of the 45 daily excess returns which were negative. A higher proportion of negative daily returns for high disagreement stocks is consistent with my extended model, as information diffuses according to the mean weight λ.

SKEW(EXRET), in the third row of Panel B, is the skewness of the daily excess returns. Similar to NEGEXRET, the skewness indicates whether the return volatility was driven by predominantly low returns, predominantly high returns, or neither. Similar to SKEW(FC), SKEW(EXRET) is larger for high RETVOL observations relative to low RETVOL observations. In sum, CUMEEXRET, NEGEXRET, and SKEW(EXRET) all indicate that high RETVOL observations tend to be driven by predominantly negative daily excess returns with infrequent, relatively high positive daily excess returns.

5.3 Turnover

I calculate SD(DTURN) as the standard deviation of the 45 daily turnover observations. In the first row of Panel C, I document that high TURN observations are characterized by significantly higher daily turnover volatility.

SKEW(DTURN), in the second row of Panel C, is the skewness of daily turnover over the 45-day estimation window. Unlike SKEW(FC) and SKEW(EXRET), SKEW(DTURN) is lower for the high disagreement (TURN) quintile relative to the low disagreement quintile, though the average is similar across all five quintiles, which limits the inference one can draw.

EARLY-LATE is calculated as the difference in the average daily turnover over the first 22 days ("early") minus the average over the second 23 days ("late"). The average EARLY-LATE is either flat or increasing over the first four TURN quintiles, with a sharp decrease at the fifth quintile. This suggests that when TURN is high, it is on average due to late increases in turnover.

6 Conclusion

In this paper, I find strong evidence that disagreement predicts the unpriced component of the surprise in fundamentals. Across both univariate disagreement sorts and two-way short-sale constraint/disagreement sorts, the pattern in earnings announcement returns is matched by a corresponding pattern in fundamentals. Conditioning on the ex-post fundamental, I find little evidence that disagreement has any predictive ability on the earnings announcement returns. These results hold across a number of different measures of disagreement, short-sale constraints, and fundamentals. Revisiting the relationship between monthly analyst dispersion and future returns documented in DMS, I find that the previously-observed negative correlation is driven virtually exclusively by serial correlation in dispersion and negative correlation between returns and contemporaneous dispersion.

To frame the results, I present a simple model linking skewness in fundamentals to disagreement and returns. I take respective predictions of the skewness model, a Miller (1977) based model, and a risk-based model to the data. Cumulatively, the results are consistent neither with a Miller story, in which disagreement drives up the current price which then falls as disagreement dissipates, nor with a risk-based model in which disagreement proxies for risk and drives the contemporaneous price down and expected returns up. By and large, the results support the predictions of the skewness model. If the mechanism in the skewness model is in fact correct, or more generally if the results are driven by some form of cognitive bias, the results raise the unanswered question of how such a pattern in returns can exist without arbitrageurs bidding it down. If the model is incorrect and the results are driven by rational agents trading optimally, the challenge is to identify what such a mechanism might look like.

Table 1: Comparison of model predictions. D_t is disagreement at date t, F_{t+1} is the fundamental realized at $t+1$, and R_t is the return at t. The expectation operator refers to the ex-post expected average, conditional on the (ex-post) observable. Given the use of ranked variables in the empirical tests, the notation "<0" and ">0" may be interpreted as "relatively low" and "relatively high", respectively.

Panel A: Earnings Announcements

		Prediction	
	Conditional on:	Skewness Model	Miller
H1	High D_t	$E[F_{t+1}] < 0$	$E[F_{t+1}] = 0$
H2	F_{t+1}	$\rho(D_t, R_{t+1}) = 0$	$\rho(D_t, R_{t+1}) < 0$

Panel B: Monthly Returns

		Prediction	
	Conditional on:	Skewness Model	Miller
H3		$\rho(D_t, D_{t+1}) > 0$	No prediction
H4	High D_t	$E[R_t] < 0$	No prediction
H4A	High $D_t \rightarrow$ High D_{t+1}	$E[R_{t+1}] < 0$	$E[R_{t+1}] = 0$
H4B	Low $D_t \rightarrow$ High D_{t+1}	$E[R_{t+1}] < 0$	$E[R_{t+1}] > 0$
H5	Low D_t	$E[R_t] > 0$	No prediction
H5A	Low $D_t \rightarrow$ Low D_{t+1}	$E[R_{t+1}] > 0$	$E[R_{t+1}] = 0$
H5B	High $D_t \rightarrow$ Low D_{t+1}	$E[R_{t+1}] > 0$	$E[R_{t+1}] < 0$

Table 2: Average earnings announcement returns and realized fundamentals, by pre-announcement disagreement. Each quarter, firms are sorted into quintiles based on their ranked disagreement. In Panel A, firms are sorted by analyst dispersion (ANADISP). In Panel B, firms are sorted by their pre-announcement return volatility (RETVOL). In Panel C, sorting is by pre-announcement daily share turnover (TURN). In Panel D, firms are sorted by their income volatility (INCVOL). BHAR is the (-1, +1) buy-and-hold raw return minus the CRSP Value-Weighted Index return. ESURP is the difference between the realized quarterly earnings per share and the mean analyst forecast, scaled by the standard deviation of the forecasts. SUE is standardized unexpected earnings, as described in Section 2. *a*, *b*, and *c* indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: ANADISP Quintiles

	1 (Low)	2	3	4	5 (High)	Low - High
BHAR	0.0025^c	0.0033^c	0.0015^c	0.0004	-0.0019^c	0.0044^c
ESURP	1.3649^c	0.8778^c	0.5051^c	0.1249^c	-0.3879^c	1.7528^c
BHAR	0.0026^c	0.0038^c	0.0021^c	0.0015^c	-0.0011^b	0.0037^c
SUE	0.0502^c	0.0181^c	-0.0075	-0.0977^c	-0.3735^c	0.4236^c

Panel B: RETVOL Quintiles

	1 (Low)	2	3	4	5 (High)	Low - High
BHAR	0.0007^c	0.0025^c	0.0039^c	0.0027^c	-0.0037^c	0.0043^c
ESURP	0.7790^c	0.7563^c	0.7222^c	0.5538^c	0.0395^b	0.7395^c
BHAR	0.0007^c	0.0028^c	0.0027^c	-0.0002	-0.0074^c	0.0081^c
SUE	-0.0002	-0.0383^c	-0.0723^c	-0.1056^c	-0.1865^c	0.1863^c

Panel C: TURN Quintiles

	1 (Low)	2	3	4	5 (High)	Low - High
BHAR	0.0015^c	0.0017^c	0.0021^c	0.0014^c	-0.0006	0.0020^c
ESURP	0.3338^c	0.5813^c	0.6406^c	0.6383^c	0.6579^c	-0.3241^c
BHAR	0.0005	-0.0003	0.0004	0.0001	-0.0023^c	0.0028^c
SUE	-0.0524^c	-0.0499^c	-0.0732^c	-0.1024^c	-0.1249^c	0.0725^c

Panel D: INCVOL Quintiles

	1 (Low)	2	3	4	5 (High)	Low - High
BHAR	0.0011^c	0.0035^c	0.0040^c	0.0019^c	-0.0013^c	0.0024^c
ESURP	0.5963^c	0.7648^c	0.6908^c	0.6112^c	0.4165^c	0.1798^c
BHAR	0.0009^c	0.0025^c	0.0005	-0.0025^c	-0.0080^c	0.0089^c
SUE	-0.0891^c	-0.0884^c	-0.0891^c	-0.0573^c	-0.0322^c	-0.0569^c

Table 3: Double-sorted portfolios based on short-sale indicative fees (FEE) and analyst dispersion (ANADISP). Following BDJKT, each quarter firms are sorted into low (bottom 30%), medium (middle 40%), and high (top 30%) groups based on their ranked FEE. Within each FEE group, firms are sorted into low, medium, and high groups based on their ranked ANADISP. Panel A reports average earnings announcement buy-and-hold abnormal returns (BHAR), and Panel B reports average earnings surprises (ESURP). a, b, and c indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Earnings Announcement Abnormal Return (BHAR)

	ANADISP Group			
	Low	Medium	High	Low - High
Fee Group				
Low	0.0036^c	0.0030^c	0.0016^c	0.0020^c
Medium	0.0041^c	0.0021^b	-0.0011	0.0052^c
High	-0.0014	-0.0044^c	-0.0054^c	0.0040^b
Low - High	0.0050^c	0.0074^c	0.0070^c	

Panel B: Earnings Surprise (ESURP)

	ANADISP Group			
	Low	Medium	High	Low - High
Fee Group				
Low	1.9137^c	1.0362^c	0.3119^c	1.6018^c
Medium	1.6646^c	0.7995^c	0.0671	1.5975^c
High	1.0587^c	0.1230^c	-0.3108^c	1.3696^c
Low - High	0.8550^c	0.9132^c	0.6228^c	

Table 4: Summary of tests for portfolios double-sorted on short-sale constraints (SSC) and disagreement (DA). Each quarter, firms are sorted into three groups (Low, Medium, and High) based on their ranked short-sale constraints. Within each short-sale constraint group, firms are then sorted into three groups based on their ranked disagreement. The first (last) three columns report the difference in average BHAR and average fundamentals between the Low and High DA (SSC) groups within a given SSC (DA) group. a, b, and c indicate significance at the 10%, 5%, and 1% levels, respectively.

		SSC Group			DA Group		
Short-Sale	BHAR/	Low	Med.	High	Low	Med.	High
Constraint	Fund'l	Diff: Low - High DA Group			Diff: Low - High SSC Group		
Panel A: Disagreement (DA) Measure = ANADISP							
FEE	BHAR	0.0020^c	0.0052^c	0.0040^b	0.0050^c	0.0074^c	0.0070^c
	ESURP	1.6018^c	1.5975^c	1.3696^c	0.8550^c	0.9132^c	0.6228^c
FEE	BHAR	0.0017^b	0.0047^c	0.0024	0.0052^c	0.0066^c	0.0059^c
	SUE	0.2318^c	0.2457^c	0.2459^c	0.1040^c	0.1276^c	0.1181^c
RETAIL	BHAR	0.0032^c	0.0026^c	0.0052^c	0.0034^c	0.0053^c	0.0055^c
	ESURP	1.4897^c	1.3726^c	1.2954^c	0.7899^c	0.7630^c	0.5956^c
RETAIL	BHAR	0.0026^c	0.0018^b	0.0046^c	0.0028^c	0.0048^c	0.0048^c
	SUE	0.2767^c	0.3360^c	0.3867^c	-0.0056	0.0139	0.1044^c
Panel B: Disagreement (DA) Measure = RETVOL							
FEE	BHAR	-0.0026^c	0.0034^b	0.0119^c	-0.0002	0.0059^c	0.0143^c
	ESURP	0.4047^c	0.4813^c	0.6444^c	0.7383^c	0.7219^c	0.9780^c
FEE	BHAR	-0.0007	0.0078^c	0.0197^c	-0.0003	0.0110^c	0.0201^c
	SUE	0.0937^c	0.0715^c	0.1290^c	0.1015^c	0.1029^c	0.1367^c
RETAIL	BHAR	0.0000	0.0005	0.0076^c	0.0021^c	0.0028^c	0.0098^c
	ESURP	0.3086^c	0.5147^c	0.6048^c	0.6001^c	0.6631^c	0.8963^c
RETAIL	BHAR	-0.0004	0.0017^b	0.0092^c	0.0014^c	0.0044^c	0.0110^c
	SUE	0.1462^c	0.1625^c	0.1739^c	0.0273^b	0.0170	0.0551^c
Panel C: Disagreement (DA) Measure = TURN							
FEE	BHAR	-0.0004	0.0013	0.0106^c	0.0011	0.0065^c	0.0121^c
	ESURP	-0.2261^c	-0.2819^c	-0.1304^a	0.6397^c	0.9765^c	0.7353^c
FEE	BHAR	-0.0009	-0.0020	0.0086^c	0.0051^c	0.0105^c	0.0146^c
	SUE	0.0512^c	-0.0002	0.0900^c	0.0957^c	0.1084^c	0.1346^c
RETAIL	BHAR	-0.0001	0.0006	0.0083^c	0.0010	0.0040^c	0.0093^c
	ESURP	-0.1830^c	-0.0790^b	0.0869^b	0.5882^c	0.7009^c	0.8581^c
RETAIL	BHAR	-0.0010	0.0018^c	0.0091^c	0.0007	0.0054^c	0.0108^c
	SUE	0.0625^c	0.1093^c	0.0638^c	0.0449^c	0.0102	0.0462^c
Panel D: Disagreement (DA) Measure = INCVOL							
FEE	BHAR	0.0005	0.0040^b	0.0099^c	0.0007	0.0075^c	0.0100^c
	ESURP	0.0672^a	-0.1449^a	0.1913^b	0.7693^c	0.7548^c	0.8934^c
FEE	BHAR	0.0018^c	0.0057^c	0.0142^c	0.0050^c	0.0121^c	0.0174^c
	SUE	-0.0444^c	-0.1963^c	-0.0912^c	0.1183^c	0.0843^c	0.0715^c
RETAIL	BHAR	0.0009	0.0020^c	0.0032^c	0.0032^c	0.0043^c	0.0056^c
	ESURP	0.0044	0.1635^c	0.1961^c	0.6839^c	0.7348^c	0.8756^c
RETAIL	BHAR	0.0013^b	0.0035^c	0.0091^c	0.0039^c	0.0060^c	0.0118^c
	SUE	-0.0411^c	-0.0595^c	-0.0408^c	-0.0066	-0.0009	-0.0064

Table 5: Fama-Macbeth regressions of earnings announcement buy-and-hold abnormal returns (BHAR), by earnings surprise (ESURP) quintiles. ANADISP and FEE are the winsorized raw (unranked) pre-announcement analyst dispersion and indicative short-sale fee, respectively. a, b, and c indicate significance at the 10%, 5%, and 1% levels, respectively

	ESURP Quintiles				
	1 (Low)	2	3	4	5 (High)
ANADISP	-0.0001	-0.0008	0.0033	0.0153^c	-0.0023
	(-0.03)	(-0.44)	(1.39)	(3.71)	(-0.32)
FEE	-0.0652	-0.1823^b	-0.1512	-0.0127	-0.1727^b
	(-1.11)	(-2.48)	(-1.62)	(-0.11)	(-2.18)
ANADISP x FEE	0.3938	0.3912^b	0.1456	-0.5019	2.3056
	(1.26)	(2.22)	(0.46)	(-0.90)	(1.64)
Constant	-0.0389^c	-0.0128^c	0.0027^c	0.0177^c	0.0356^c
	(-27.97)	(-14.41)	(3.43)	(17.40)	(30.11)
Observations	21395	21389	21586	21591	21593
R^2	0.017	0.014	0.018	0.027	0.017

Table 6: Fama-Macbeth regressions of earnings announcement buy-and-hold abnormal returns (BHAR), by realized fundamental quintiles. Coefficient estimates from regressing BHAR on disagreement (DA) and its interaction with the short-sale constraint (DA×SSC). Shaded cells indicate coefficients consistent with the Miller (1997) overpricing theory. a, b, and c indicate significance at the 10%, 5%, and 1% levels, respectively.

SSC/FUND Measure	Independent Variable	Fundamental (FUND) Quintile 1 (Low)	2	3	4	5 (High)
Panel A: Disagreement Measure (DA) = ANADISP						
FEE/ESURP	DA	-0.0001	-0.0008	0.0033	0.0153^{c}	-0.0023
	DA x SSC	0.3938	0.3912^{b}	0.1456	-0.5019	2.3056
FEE/SUE	DA	-0.0026	-0.0022	-0.0016	0.0096	0.0079
	DA x SSC	0.2622	0.2312	0.5606	-1.9394	-0.3878
RETAIL/ESURP	DA	0.0022	0.0044	0.0054^{a}	0.0044	0.0219^{a}
	DA x SSC	-0.0021	-0.0076	-0.006	0.0079	-0.0117
RETAIL/SUE	DA	-0.0077^{b}	-0.0091	-0.0007	0.0048	-0.007
	DA x SSC	0.0114^{a}	0.0162	0.0018	-0.0036	0.0223^{a}
Panel B: Disagreement Measure (DA) = RETVOL						
FEE/ESURP	DA	-0.2944^{c}	-0.2051^{c}	0.0476	0.3915^{c}	0.4896^{c}
	DA x SSC	3.2741	-3.0959	-14.2832^{a}	-9.0676	2.6653
FEE/SUE	DA	-0.3458^{c}	-0.3701^{c}	-0.1685^{a}	-0.0262	-0.0105
	DA x SSC	2.0393	3.9544	-2.689	-5.1619	-3.1458
RETAIL/ESURP	DA	-0.2608	-0.0644	0.0368	0.3733^{c}	0.5508^{c}
	DA x SSC	-0.19	-0.2895	-0.1788	-0.4354^{b}	-0.3214
RETAIL/SUE	DA	-0.3379^{b}	-0.0892	0.0741	0.0436	0.4260^{c}
	DA x SSC	-0.0078	-0.2053	-0.256	-0.0109	-0.4249^{b}
Panel C: Disagreement Measure (DA) = TURN						
FEE/ESURP	DA	-0.0005^{b}	-0.0003^{c}	-0.0002	0.0002	0.0001
	DA x SSC	-0.0068	-0.0251^{a}	-0.0335	-0.0238	0.0016
FEE/SUE	DA	-0.0001	0.0000	0.0001	-0.0003^{a}	-0.0002^{a}
	DA x SSC	0.0068	-0.0100	-0.0078	0.0257	-0.0127
RETAIL/ESURP	DA	-0.0004	-0.0006	0.0001	-0.0006	0.0007^{a}
	DA x SSC	-0.0005	0.0001	-0.0009	0.0007	-0.0003
RETAIL/SUE	DA	-0.0011^{b}	0.0004	0.0007	0.0001	0.0011^{c}
	DA x SSC	0.0011^{a}	-0.0009^{a}	-0.0015^{a}	-0.0004	-0.0024^{c}
Panel D: Disagreement Measure (DA) = INCVOL						
FEE/ESURP	DA	-0.0841^{a}	-0.0782^{b}	-0.1039	0.0187	0.1151^{b}
	DA x SSC	6.1860^{b}	5.1881	8.8721	-7.7627	-17.2149
FEE/SUE	DA	-0.0868^{b}	-0.0925^{b}	-0.0288	-0.0243	-0.0755
	DA x SSC	0.4104	3.3506^{a}	1.8545	-1.2916	3.5393
RETAIL/ESURP	DA	-0.0978	-0.2604^{b}	0.0081	-0.0212	0.1676^{a}
	DA x SSC	0.0126	0.3266^{a}	-0.0138	0.1409	-0.1886
RETAIL/SUE	DA	-0.0645	-0.0783	0.0164	0.0803	0.2048^{b}
	DA x SSC	-0.0394	0.0301	-0.0654	-0.1	-0.2600^{b}

Table 7: Mean $t+1$ Excess Returns for (ANADISP_t, ANADISP_{t+1}) Quintile Pairs. Each month, firms are sorted into quintiles by their analyst dispersion. Firms are then allocated to unequal portfolios based on their t and $t+1$ dispersion quintiles. The mean $t+1$ excess return is reported for each $(t, t+1)$ quintile pair. a, b, and c indicate significance at the 10%, 5%, and 1% values, respectively.

ANADISP_t	ANADISP_{t+1} Quintile					
Quintile	1 (Low)	2	3	4	5 (High)	All
1 (Low)	0.0083^c	0.0034^c	0.0046^c	0.0011	-0.0042^a	0.0067^c
2	0.0052^c	0.0015^c	-0.0019^c	-0.0073^c	-0.0231^c	0.0004^a
3	0.0054^c	0.0027^c	0.0017^c	-0.0026^c	-0.0230^c	0.0002
4	0.0063^c	0.0054^c	0.0032^c	0.0016^c	-0.0108^c	0.0003
5 (High)	0.0072^c	0.0005	0.0010	0.0050^c	-0.0030^c	-0.0018^c
All	0.0080^c	0.0021^c	0.0017^c	0.0010^c	-0.0050^c	

Table 8: Average $t + 1$ excess returns, conditional on the t to $t + 1$ change in the monthly analyst dispersion (ANADISP) quintile. Each month, firms are sorted into quintiles based on their ranked ANADISP. For a given firm, the $t + 1$ change in dispersion is measured as its ANADISP quintile in month $t + 1$ minus its ANADISP quintile in month t. a, b, and c indicate significance at the 10%, 5%, and 1% levels, respectively.

	Excess Return$_{t+1}$	Obs.
-4 (Decreasing Disp.)	0.0072^c	5089
-3	0.0049^c	9810
-2	0.0043^c	23679
-1	0.0039^c	85671
0 (No Change)	0.0021^c	544380
+1	-0.0033^c	81862
+2	-0.0061^c	25933
+3	-0.0052^c	10945
+4 (Increasing Disp.)	-0.0042^a	5243

Table 9: Fama-MacBeth regressions on month $t+1$ excess returns. ΔANADISP is the $(t, t+1)$ monthly change in analyst dispersion. ANADISP_{t+1} is the level of analyst dispersion at $t+1$. a, b, and c indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
ΔANADISP	-0.0034^b	-0.0010
	(-2.42)	(-1.37)
ANADISP_{t+1}		-0.0033^c
		(-5.12)
Constant	0.0015	0.0021^b
	(1.36)	(2.01)
Observations	792612	792612
R^2	0.003	0.010

Table 10: Characteristics of Disagreement. This table reports the averages across quintiles for a given disagreement measure. For a given observation, the variables are calculated over the corresponding 45-day pre-announcement estimation window. NUMANALYSTS is the number of unique analysts. SKEW(ANADISP) is the skewness of the analysts' forecasts. BELOWMEDIAN is the proportion of forecasts which were below their respective trailing five-forecast medians. LOWLATE is the proportion of below-median forecasts ("low") which were made after the median analyst announcement date ("late"). CUMEEXRET is the cumulative 45-day buy-and-hold excess return. NEGEXRET is the fraction of the 45 daily excess returns which were negative. SKEW(EXRET) is the skewness of the daily excess returns. SD(DTURN) is the standard deviation of the daily turnover. SKEW(DTURN) is the skewness of the daily turnover. EARLY-LATE is the difference in the average daily turnover over the first 22 days ("early") minus the average over the second 23 days ("late"). *a*, *b*, and *c* indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: ANADISP Quintiles

	1 (Low)	2	3	4	5 (High)	Low - High
NUMANALYSTS	7.0060	7.3954	6.9441	6.3095	5.6513	1.3546^c
LOWLATE	0.2493	0.3548	0.3899	0.4152	0.4644	-0.2151^c
SKEW(FC)	-0.0099	-0.0003	0.0017	0.0667	0.1701	-0.1800^c
BELOWMEDIAN	0.4444	0.4913	0.5288	0.5654	0.6164	-0.1721^c

Panel B: RETVOL Quintiles

	1 (Low)	2	3	4	5 (High)	Low - High
CUMEEXRET	0.0023	0.0052	0.0047	-0.0013	0.0100	-0.0077^c
NEGEXRET	0.5071	0.5095	0.5142	0.5211	0.5318	-0.0247^c
SKEW(EXRET)	0.1091	0.1874	0.2508	0.3307	0.5889	-0.4798^c

Panel C: TURN Quintiles

	1 (Low)	2	3	4	5 (High)	Low - High
SD(DTURN)	1.2223	2.4173	3.6175	5.9114	18.8605	-17.6382^c
SKEW(DTURN)	2.6077	2.3096	2.2125	2.2813	2.4433	0.1645^c
EARLY-LATE	0.0226	0.0169	0.0383	0.0817	-0.3670	0.3896

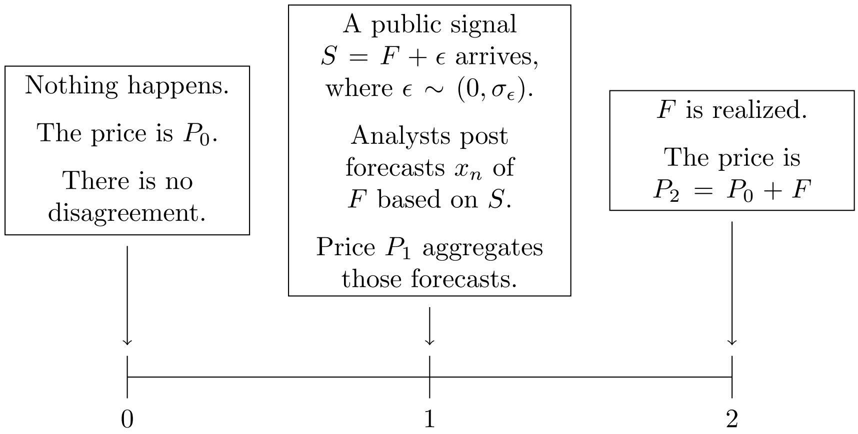

Figure 1: Timeline of the model

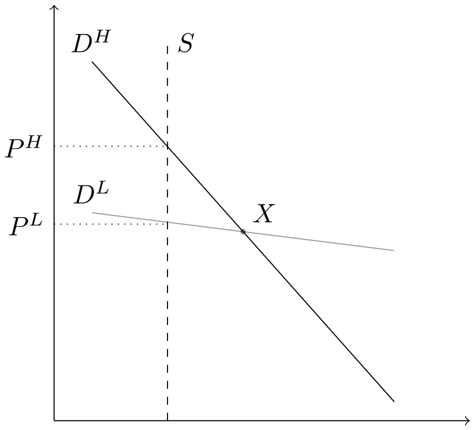

Figure 2: Inelastic supply and downward-sloping demand curves in the market for a security, per Miller (1977).

References

Abarbanell, J. S. (1991). Do analysts' earnings forecasts incorporate information in prior stock price changes? *Journal of Accounting and Economics*, *14*(2), 147–165.

Avramov, D., Chordia, T., Jostova, G., & Philipov, A. (2009). Dispersion in analysts' earnings forecasts and credit rating. *Journal of Financial Economics*, *91*(1), 83–101.

Berkman, H., Dimitrov, V., Jain, P. C., Koch, P. D., & Tice, S. (2009). Sell on the news: Differences of opinion, short-sales constraints, and returns around earnings announcements. *Journal of Financial Economics*, *92*(3), 376–399.

Brown, P., Foster, G., & Noreen, E. (1985). *Security analyst multi-year earnings forecasts and the capital market* (No. 21). Amer Accounting Assn.

Carlin, B. I., Longstaff, F. A., & Matoba, K. (2014). Disagreement and asset prices. *Journal of Financial Economics*, *114*(2), 226–238.

Cen, L., Wei, K. J., & Yang, L. (2016). Disagreement, underreaction, and stock returns. *Management Science*, *63*(4), 1214–1231.

Collins, D. W., & Kothari, S. (1989). An analysis of intertemporal and cross-sectional determinants of earnings response coefficients. *Journal of accounting and economics*, *11*(2-3), 143–181.

David, A. (2008). Heterogeneous beliefs, speculation, and the equity premium. *The Journal of Finance*, *63*(1), 41–83.

De Bondt, W. F., & Thaler, R. H. (1990). Do security analysts overreact? *The American Economic Review*, 52–57.

Dechow, P. M., Hutton, A. P., & Sloan, R. G. (2000). The relation between analysts' forecasts of long-term earnings growth and stock price performance following equity offerings. *Contemporary Accounting Research*, *17*(1), 1–32.

Diether, K. B., Malloy, C. J., & Scherbina, A. (2002). Differences of opinion and the cross section of stock returns. *The Journal of Finance*, *57*(5), 2113–2141.

Dreman, D. N., & Berry, M. A. (1995). Analyst forecasting errors and their implications for security analysis. *Financial Analysts Journal*, 30–41.

Grinblatt, M., Jostova, G., & Philipov, A. (2017). Analyst bias and mispricing. *working paper*.

Hong, H., Lim, T., & Stein, J. C. (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance*, *55*(1), 265–295.

Hong, H., & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of finance*, *54*(6), 2143–2184.

Johnson, T. C. (2004). Forecast dispersion and the cross section of expected returns. *The Journal of Finance*, *59*(5), 1957–1978.

Kondor, P. (2012). The more we know about the fundamental, the less we agree on the price. *The Review of Economic Studies*, *79*(3), 1175–1207.

Lahiri, K., & Sheng, X. (2008). Evolution of forecast disagreement in a bayesian learning model. *Journal of Econometrics*, *144*(2), 325–340.

Lim, T. (2001). Rationality and analysts' forecast bias. *The Journal of Finance*, *56*(1), 369–385.

Michaely, R., & Womack, K. L. (1999). Conflict of interest and the credibility of underwriter analyst recommendations. *Review of financial studies*, *12*(4), 653–686.

Milgrom, P., & Stokey, N. (1982). Information, trade and common knowledge. *Journal of economic theory*, *26*(1), 17–27.

Miller, E. M. (1977). Risk, uncertainty, and divergence of opinion. *The Journal of finance*, *32*(4), 1151–1168.

Scharfstein, D. S., & Stein, J. C. (1990). Herd behavior and investment. *The American Economic Review*, 465–479.

Scherbina, A. (2008). Suppressed negative information and future underperformance. *Review of Finance*, 533–565.

Stickel, S. E. (1990). Predicting individual analyst earnings forecasts. *Journal of Ac-*

counting Research, 409–417.

Trueman, B. (1994). Analyst forecasts and herding behavior. *The Review of Financial Studies*, *7*(1), 97–124.

Tversky, A., & Kahneman, D. (1975). Judgment under uncertainty: Heuristics and biases. In *Utility, probability, and human decision making* (pp. 141–162). Springer.

Varian, H. R. (1985). Divergence of opinion in complete markets: A note. *The Journal of Finance*, *40*(1), 309–317.

Veenman, D., & Verwijmeren, P. (in press). Do investors fully unravel persistent pessimism in analysts' earnings forecasts? *The Accounting Review*.

Welch, I. (2000). Herding among security analysts. *Journal of Financial economics*, *58*(3), 369–396.

Zhang, X. (2006). Information uncertainty and stock returns. *The Journal of Finance*, *61*(1), 105–137.