PI1. Eugene Kandel Application No. – 1724/23

Detailed Description of the Research Program

1. Scientific Background:

Information Economics theory focuses on the effects of information asymmetry between agents on the equilibrium of various settings, including prices and the volume of trading in securities. Grossman (1976), Aumann (1976), Milgrom, Stokey (1982), and Tirole (1982) demonstrate that when there is common knowledge of the structure of the market and agents agree about the interpretation of information, no trade will occur in the market as the equilibrium price reveals all the private information of the agents. To make the no-trade result compatible with reality, Grossman and Stiglitz (1980), pioneered the noisy rational expectation models, where some trades are initiated due to liquidity needs or other exogenous reasons, thus preventing full revelation of private information.

Another strand of literature focuses on the difference of opinions, which refers to differences in the models (likelihood functions) used by different actors to interpret the incoming (possibly identical) information. Harrison and Kreps (1978), Varian (1985), Harris and Raviv (1993), Kandel and Pearson (1995), Kandel and Zilberfarb (1999), Kim and Verrecchia (1994), Banerjee and Kremer (2010), Banerjee (2011), Kondor (2012) and others, construct models in which agents see the same information, yet interpret it differently by employing differing models of the world. They term it “Difference of Opinions” since the differences persist even when agents are exposed to the same information, i.e., investors can agree to disagree. No-Trade theorems do not apply in this case. Kandel and Pearson (1995), Kandel and Zilberfarb (1999), Bannerjee (2011), Cookson and Niessner (2020), Fischer, Kim, and Zhou (2021) and others, provide empirical evidence that rules out purely “Difference of Information” models, suggesting that difference of opinions has a significant presence and influences markets. In recent years, it seems that such differences of opinions have become even more prevalent, despite, or maybe due to, the surge in publicly available information from various sources. Any researcher who attempts to test the effect of traders’ disagreement (from either source) on the equilibrium in financial markets faces two significant challenges. The first is due to the lack of data on investor disagreement, which forces researchers to use disagreement in readily available analysts’ EPS forecasts as a proxy for the investors’ disagreement. The validity of this proxy is difficult to test empirically due to the lack of investor beliefs data. Goetzmann and Massa (2005) argue that analysts’ forecasts represent professional analysts’ opinions but may not directly reflect investors’ opinions. They construct a difference of opinion measure using the differences in transactions of investors from different classes, which are defined based on specific characteristics such as income, age, and profession. They find that their investors-based measure Granger-causes the standard measure of dispersion of opinion among analysts and conclude that analysts report the already existing market sentiment. Recent work by Cookson and Niessner (2020) tries to overcome this challenge by using data from social media platforms. Interestingly, they find low correlation between their disagreement measure and the extant measures based on analysts' forecasts dispersion.

The second challenge is designing a measure that theoretically represents analysts' disagreement and is measured more precisely than the widely used measure in the literature. Such measure must capture the unexpected component of disagreement, which is the most relevant for testing hypotheses related to trade and prices of securities.

The goal of this project is to try and remedy both shortcomings. First, we offer a theoretically supported measure of disagreement that could potentially affect trade. Note that, as well accepted in Finance, trade and prices cannot be affected by a measure that is predictable ahead of time based on public information, since trading based on such a measure should have happened in the past when the public information arrived and should already be incorporated in prices. Our proposed measure captures *the unexpected change in disagreement*, which addresses the shortcomings in the standard measure of disagreement that is based on analysts' EPS forecasts - pioneered by Diether, Malloy, and Scherbina (2002) (DMS). Our measure of disagreement is sound theoretically yet still based on the available analysts' forecasts data. We empirically compare the performance of the two measures and show how they address theoretical and empirical challenges. We plan to utilize our measure to test a variety of hypotheses already presented in the literature that used the DMS measure.[1]

To test whether disagreement among analysts does not necessarily reflect disagreement among investors, we plan on using a novel proprietary data set that combines analysts' forecasts with data on retail investors' trading and the information that they are observing before their trade. The source of data is TipRanks – an Israeli fintech platform that aggregates multiple sources of information about US equities and presents them to over half a million US retail investors. Tens of thousands of US retail investors connect their brokerage accounts to the platforms, so we can track their holdings and trades. Hundreds of thousands more have active fiat trading accounts on the platform. We have obtained approval from TipRanks to work with this data. Individual level retail investors' data is very difficult to obtain, and in this case the data allows us to match trades with various information measures displayed to investors on the TipRanks platform. This combination represents a unique opportunity to perform tests that were not previously possible due to the lack of data.

[1] The following papers touch on similar issues and have been instrumental in our thinking in this project: Gervais and Odean (2001), Abarbanell and Lehavy (2003), Garfinkel and Sokobin (2006), Scheinkman and Xiong (2003), Hong and Stein (2007), Garfinkel (2009), Xiong (2013), Cen, Wei, and Yang (2017). Chang, Ljungqvist, and Tseng (2021), and Chang et al (2022). Due to space limitations, we are not expanding on these in this proposal, but will discuss these in the paper.

2. Objectives and Expected Significance of the Research

The most common measures of disagreement are based on analysts' forecasts dispersion. These measures of disagreement among analysts are used to test hypotheses and as controls in thousands of academic papers. Unfortunately, the most popular measures suffer from several theoretical shortcomings, casting significant doubts on the interpretation of tests based on these measures. Creating a theoretically sound measure of disagreement among analysts by explicitly addressing these shortcomings, as well as validating it, can create an important tool for future research, and advance our understanding of the relation between disagreement and trade. Accordingly, the first objective of this project is to introduce a theoretically-sound measure of analysts' disagreement that is based on readily available data on analysts' EPS forecasts, and empirically specify its characteristics, and its relation to trading behavior: e.g., concurrent and future volume, returns, and volatility.

The second objective of our project is to test the validity of analysts' disagreement as a proxy for retail investors' disagreements. We will try to assess the validity directly utilizing the novel dataset we plan to construct using TipRanks' data, alongside methodologies from several relevant papers, such as Goetzman and Massa (2005) and Cookson and Niessner (2020). TipRanks' data is unique as it provides us with a match between the arrival of new information observed by a trader with that trader's directional order flow, for a large number of retail investors. Retail investors are of special interest in this case, as they typically lack their own research capabilities, and thus rely on the publicly available information. The validation of this proxy has significance to the vast literature using analysts' forecasts and will provide important guidance for future related research.

3. Detailed Description of the Proposed Research

<u>3.1 Working Hypotheses:</u>

1. Our proposed measure of disagreement among analysts has significant theoretical and empirical advantages for the study of any trade related phenomena, relative to the most widely used measure in the literature. We provide some empirical evidence supporting this hypothesis and plan to provide more.
2. The standard assumption in Finance and Accounting literature is that disagreement among analysts is a good proxy for investors' disagreement. We plan to test this general hypothesis by using a novel dataset of information arrival and retail investors' behavior and validating the new analysts' disagreement measure we have developed.

<u>3.2 Research Design and Methods:</u>

3.2.1 Design and Validation of the New Measure

We construct a measure of the unexpected changes in levels of disagreement among analysts that forecast EPS. Only the unexpected portion of the change in disagreement, rather than its level is likely to drive trading, and potentially affect volume, returns, or volatility.

As DMS and others, we base our measure on the standard deviation (dispersion) of the analysts' forecasts of the annual EPS (our measure can be adapted to other forecasts as well). The difference is in how we compute and normalize it. We conjecture that in the short window following the earning announcement, there is a lower probability of other significant public information releases. At the same time, many analysts issue new forecasts during that window, eliminating the problem of stale forecasts. Thus, we only use forecasts issued during the first 20 trading days starting from the second trading day after the earning announcement for stock *i* in quarter *q* of year *t*. We further conjecture that the level of dispersion contains a predictable component based on the identity of the firm, and the quarter. Thus, we scale the dispersion by the average of the standard deviations of analysts' forecasts calculated for stock *i* in the same corresponding quarter *q* over the previous three years:

$$Unexpected\ Disagrement\ Measure_{i,q,t} = \frac{\sigma(eps\_forecasts)_{i,q,t}}{\frac{1}{3}\sum_{j=1}^{3}\sigma(eps\_forecasts)_{i,q,t-j}]}$$

This measure captures the unexpected change in disagreement, which can potentially drive trade. This is in stark difference with DMS, that measure disagreement as the standard deviation of analysts' annual EPS forecasts divided by the absolute value of the mean forecast, which captures the absolute level of analysts' disagreement about the future EPS of a stock every month, without worrying about the predictability.[2]

As stated above, we conjecture that a significant part of the disagreement level is predictable ahead of time. First, following Miller (1977) and Johnson (2004),[3] we predict that some firms operate in business environment or sector that are more difficult to predict or are more likely to be subject to different interpretations, thus some stocks would exhibit a much larger disagreement. Under this conjecture, the firm's idiosyncratic features can predict the future degree of disagreement, thus we must remove the firm fixed effect to capture the unexpected part. Our measure does that as we normalized the numerator by the average level of disagreement in the corresponding quarter over the

[2] Berkman et al. (2009) and others also use the level measures without the discussion of predictability or public information arrival.

[3] Johnson's (2004) interpretation also hinges on the assumption of unexpected change in disagreement, as the option value should not be affected by the predicted levels of disagreement/uncertainty.

past three years. In contrast, DMS scales by the consensus forecast, which does not remove the predictable component.

In addition, analysts face different degrees of uncertainty about the annual earnings over the course of the year. In the first months after the annual report announcement, they are uncertain about the entire year's earnings (all four quarters), while in the last months they are uncertain only about the last quarter's earnings. This would imply that their disagreement levels regarding the annual earnings predictably decline as the fiscal year progresses. Moreover, since firms have differing fiscal year ends, the month of April is early in the year for the December-ending fiscal year firms, while very late for those ending their fiscal year in June. Ignoring this may generate a very different composition of firms in disagreement quintiles based on nothing more than their fiscal year. Knowing the quarter of the year and the fiscal year-end makes part of the disagreement predictable, thus our measure, unlike DMS, controls for that part by normalizing the analysts' disagreement about a firm by the average of past disagreements about the same firm during the same quarter - a simple way of capturing the unexpected component.

There is another theoretical concern that arises in general when using a measure of intertemporal dispersion to proxy for disagreement. Belief formation is a temporal concept, thus must be measured at the same time (conditional on the same public information), otherwise, the information sets may predictably differ across observations, contaminating the measurement. To illustrate, suppose that four analysts are in perfect agreement. Two of them issue their forecasts first, and then there is an unexpected arrival of public information that changes the expected annual EPS. The two other analysts issue their forecasts immediately after, while the first two don't. If we calculate the variance of forecasts over the course of the month, it will indicate disagreement that is proportional to the squared change in the consensus. This simple example shows that public information arrival may generate the appearance of disagreement when one does not exist. More formally, if consensus-moving public information about a company (or a sector) arrives during the month, the variance of analysts' forecasts calculated over the entire month can be represented as a linear function of the variance of forecasts prior to the arrival of information, variance following the arrival, and the squared change in the mean forecast following the arrival. When the arriving public signal is significant, this effect may be the main driver of changes in the DMS measure of dispersion, dramatically reducing its theoretical validity as a proxy for the true disagreement. Many firms in high disagreement quintile are actually firms with significant expectations-moving news (in either direction), thus DMS results must be then interpreted in light of a plethora of possible effects associated with a sudden release of public information and its processing by analysts.

To address the last concern, our proposed measure is calculated over a short period of time after the arrival of the most significant (on average) public information event – the earnings announcement. Another benefit of this particular time window is that it is characterized by issuance of forecasts by many analysts in a short time window. While this does not eliminate the possibility of arrival of additional public information, we conjecture that it makes it less pronounced and idiosyncratic. Below we evaluate both measures, ours and DMS, using the same methodology.

Berkman et al. (2009) also focus on earnings announcement. They postulate that earnings announcements reduce differences of opinion among investors, and consequently, due to short sale constraints frictions suggested by Miller (1977), announcements should reduce overvaluation. They use five proxies and find that high disagreement stocks earn significantly lower returns around earnings announcements, especially those that are the most difficult to short. The use of earnings announcement as a major source of public information is common to our approach in the first part of our project and theirs, however, among many other differences, we study the disagreement AFTER the earnings announcement. This enables us to avoid the informational effect of earnings announcement (ahead and during the event), which incorporates many major confounding effects on returns. Moreover, their hypothesis relies on an assumption that information event decreases disagreement, which is not at all obvious. While the information event reduces uncertainty, its effect on disagreement is not clear given the findings in Kandel and Pearson (1995), Kandel and Zilberfarb (1999) and Kim and Verrecchia (1997). To better understand the effect of earnings announcements on disagreement, we intend to replicate some of Berkman et al (2009) results with our measure.

3.3 Preliminary Results

We compare the performance of our measure relative to the measure of DMS in several tests corresponding to the theoretical underpinnings described above. [4]

Both measures utilize readily available analysts' annual EPS forecasts, provided by IBES. DMS measures disagreement as the standard deviation of the annual EPS forecasts scaled by the absolute value of the mean forecast.[5] We replicated DMS results for the last decade 2010-2020,[6] using, as they do, the Unadjusted Summary History data file from IBES. Table 1 Panel A presents the DMS mean dispersion in analysts' forecasts by quintiles of size and disagreement for their time period (1983-

[4] DMS study the relation between their analysts' disagreement measure and subsequent returns, controlling for the firm size. The portfolio of stocks with the lowest quintile of disagreement among analysts during a certain month, delivers a significant 1.37% higher return over the subsequent month, relative to stocks in the highest disagreement quintile. DMS methodology and interpretation of their results continue to be widely relied on in Financial and Accounting research as controls or main variables. We therefore use the methodology of DMS as a representative of a large literature using disagreement among analysts to test various hypotheses. Avramov et al. (2009) show that DMS findings are driven by a small number of firms whose debt have been recently downgraded.

[5] Such scaling generates some extreme observations, which DMs truncate.

[6] We intend to extend the sample period to 1983, so it is comparable directly with DMS findings.

2000), and Panel B presents our replication of the mean dispersion for the last decade - 2010-2020. The differences in disagreement between the highest and the lowest dispersion quintiles in DMS paper are enormous: in the highest dispersion quintile the disagreement is between 30 (for largest firm size quintile) to 125 (for smallest firm size quintile) times larger than in the lowest disagreement quintile. In the 2010-2020 sample these differences decline, but they are still significant: 36-51 times. Notice, that the disagreement predictably declines with firm size across size quintiles, but the same logic applies to individual firms within quintiles, which suggests predictability ahead of time.

Panel C presents the replication of DMS in 2010-21 using only the sample of firms with December fiscal year-end. The results are very similar to those in Panel B. Finally, we present our measure, calculated for the sample of firms with the fiscal year ending in December. The results are dramatically different - the differences across size quintiles are on the order of magnitude of 8-11 times, declining as the firm size increases. This implies that the remaining variance within each size quintile is rather limited. This is due to the fact that our measure is scaled by the past levels of disagreement for the same firm in the same quarter, thus the firm and period fixed effects are removed, leaving only the "unexpected" component. Moreover, our measure contains much less mismeasurement due to the public information arrival, and hence does not capture public information as a component of disagreement – resulting in further reduction in the scale of disagreement across quintiles.

Table 1 Panel A: DMS Table II Panel A – Mean Dispersion by Quintiles

Mean Dispersion						
	Size Quintiles					
Dispersion Quintiles	$S1$	$S2$	$S3$	$S4$	$S5$	All Stocks
$D1$ (low)	0.010	0.011	0.012	0.014	0.014	0.012
$D2$	0.039	0.033	0.030	0.028	0.025	0.030
$D3$	0.081	0.062	0.053	0.047	0.039	0.053
$D4$	0.172	0.125	0.103	0.086	0.067	0.105
$D5$ (high)	1.256	0.963	0.813	0.722	0.462	0.852

Source: Diether, Malloy & Scherbina (2002)

Table 1 Panel B: DMS replication in 2010-2020 for the entire sample – Mean Dispersion by Quintiles

	Size Quintiles				
Dispersion Quintiles	**S1**	**S2**	**S3**	**S4**	**S5**
D1 (low)	0.016	0.014	0.012	0.011	0.008
D2	0.045	0.034	0.027	0.022	0.015
D3	0.086	0.062	0.047	0.039	0.025
D4	0.175	0.125	0.096	0.077	0.051
D5 (high)	0.833	0.630	0.524	0.442	0.275
D5/D1	50.9	44.7	44.0	41.9	35.6

Table 1 Panel C: DMS replication 2010-2020 for the sample of firms with December fiscal year-end – Mean Dispersion by Quintiles

	Size Quintiles				
Dispersion Quintiles	S1	S2	S3	S4	S5
D1	0.019	0.015	0.014	0.012	0.009
D2	0.047	0.035	0.030	0.024	0.017
D3	0.088	0.065	0.054	0.043	0.031
D4	0.189	0.133	0.131	0.086	0.063
D5	0.826	0.643	0.574	0.451	0.327
D5/D1	43.5	42.9	41.0	37.6	36.3

Table 1 Panel D: New measure calculated in 2010-2020 for the sample of firms with December fiscal year-end – Mean Dispersion by Quintiles

	Size Quintiles				
Dispersion Quintiles	S1	S2	S3	S4	S5
D1	0.339	0.358	0.373	0.391	0.415
D2	0.670	0.724	0.731	0.746	0.745
D3	1.030	1.098	1.076	1.077	1.041
D4	1.597	1.677	1.619	1.580	1.499
D5	3.924	4.075	3.963	3.855	3.488
D5/D1	11.6	11.4	10.6	9.9	8.4

We next test whether the firm identity and the associated current disagreement about the future EPS can be used to predict the future disagreement. Table 2 presents a transition matrix: the probability that a stock in a disagreement quintile at month t moves to another disagreement quintile at month t+1. Of special interest for us is the diagonal coefficient that represents the probability that a firm stays in the same disagreement quintile. Panel A presents pooled data from 2010-21 across all firm sizes – the probability of a stock in the low/high disagreement quintile to remain in the same quintile is 71/80%. At the same time, the probability of moving to the highest/lowest quintile is around 1%. Clearly, the identity of the firm is important in predicting its DMS disagreement measure. Assuming random assignment of stocks into quintiles every month does not seem reasonable, as some monthly variation is dominated by the firm effect.

We test the robustness of these findings by only considering firms with December fiscal year-end in Panel B – the results are almost identical thus it is not a month-specific phenomenon. The results are the same for a sample of firms in the smallest size quintile (not presented to save space). Panel C presents *quarterly* (rather than monthly) data for December fiscal year firms and the results are even stronger: even after 3 months, the probability of staying in the lowest/highest quintile is 57/68%, and the probability for a reversal is still around 1.5%. Clearly the position in a quintile is very persistent, thus predictable. It indicates that using monthly data rather than quarterly data does not add much variation in movement between quintiles.

Panel D presents the transition probabilities across quintiles over adjacent quarters, using our measure. Compared to Panel C the probability of staying within the extreme disagreement quintile declines from 57/68% to 40%; at the same time the extreme reversal rises from 1.5% to 9%. The diagonal probabilities in the middle are not significantly different from a random allocation, i.e., not predictable. While some persistence remains (we will explore its sources in this project), its extent is much lower.

Table 2: Transition matrix between the quintiles of disagreement - 4 panels

Panel A: DMS measure; full pooled sample of all companies, monthly data.

Disagreement quintile in month t	Disagreement quintile in month t+1 for the same firm				
	D1	D2	D3	D4	D5
D1	**71.3%**	17.4%	6.7%	3.3%	1.3%
D2	19.7%	**57.5%**	16.4%	5.0%	1.5%
D3	6.2%	19.2%	**56.3%**	15.1%	3.3%
D4	2.5%	4.9%	17.8%	**61.5%**	13.3%
D5	1.0%	1.2%	3.0%	15.1%	**79.7%**

Panel B: DMS measure; all companies with fiscal year ending in December, monthly data

Disagreement quintile in month t	Disagreement quintile in month t+1 for the same firm				
	D1	D2	D3	D4	D5
D1	**72.6%**	17.2%	6.1%	2.9%	1.2%
D2	18.3%	**58.9%**	16.4%	5.0%	1.5%
D3	5.4%	18.3%	**57.5%**	15.4%	3.4%
D4	2.2%	4.4%	17.2%	**62.7%**	13.6%
D5	0.91%	1.1%	2.8%	14.6%	**80.6%**

Panel C: DMS measure; all companies with fiscal year ending in December, quarterly data

Disagreement quintile in quarter t	Disagreement quintile in quarter t+1 for the same firm				
	D1	D2	D3	D4	D5
D1	**56.9%**	26.6%	10.5%	4.4%	1.6%
D2	27.2%	**39.1%**	22.8%	8.4%	2.5%
D3	9.8%	24.6%	**38.7%**	20.7%	6.3%
D4	3.4%	8.0%	22.6%	**45.4%**	20.6%
D5	1.5%	2.1%	5.8%	22.1%	**68.5%**

Panel D: Our measure; all companies with fiscal year ending in December, quarterly data

Disagreement quintile in quarter t	Disagreement quintile in quarter t+1 for the same firm				
	D1	D2	D3	D4	D5
D1	**40.9%**	22.6%	16.2%	11.2%	9.1%

D2	22.3%	**25.5%**	22.2%	18.2%	11.8%
D3	15.5%	22.8%	**24.9%**	22.2%	14.7%
D4	11.8%	17.7%	21.9%	**26.7%**	21.9%
D5	9.6%	11.9%	15.8%	23.1%	**39.6%**

Next, we test whether the combination of the month and the fiscal year predict the level of disagreement. Publicly traded firms in the US can choose their own fiscal year-end. In Table 3 we present the 5 most common fiscal year-end months, which comprise 94.5% of all firms. December is the most likely to be chosen, but a non-trivial number of firms choose January, March, June, and September. Since firms differ in terms of the analysts' activity, the distribution of observations across different fiscal years is only slightly different than the distribution of firms. However, the distribution of observations by month differs dramatically depending on the fiscal year-end. In fact, across all firms, analysts stay mostly silent during the month in which the fiscal year ends and the following month, i.e., the last two months prior to the annual earnings announcement. For December fiscal year firms, only 0.56% of all observations throughout the year occur in December-January, as opposed to 16.5% we would have expected if the allocation was random. During these months, instead of 79% of observations, December fiscal year firms represent only 10%, skewing the composition of disagreement portfolios.

Limiting the sample to only December fiscal year firms, Panel B Column (1) of Table 3 shows that the DMS disagreement measure predictably declines as the year progresses from March, which is the month after the annual earnings announcement, until November. The difference between high and low disagreement is about 30% on average. The results suggest that the disagreement levels are predictably determined not only by the firm identity but also by the time till the fiscal year-end, thus any measure that captures the surprise disagreement must account for the time of the fiscal year. Our measure does that by scaling the measure of dispersion by the same-quarter measure, averaged over the last three years. As a result, Panel B Column (2) demonstrates that our measure does not display the predicted decline in dispersion over the course of the year.

Table 3 Panel A: Observations of firms with varying fiscal year, monthly

	Five Most Common Fiscal Year-End Months				
	December	**January**	**March**	**June**	**September**
% of firms in the sample	81%	3.0%	3.3%	3.6%	3.6%
% of observations in the sample	79%	3.4%	3.3%	3.6%	4.3%
Two months prior to the annual announcement	December – January	January-February	March-April	June-July	September-October
% of all annual observations for these firms occurring in the above two months	0.56%	1.21%	0.81%	0.16%	0.09%
% of all observations during these months for the firms with all fiscal year ends	10.75%	0.46%	0.14%	0.03%	0.02%

Table 3 - Panel B: The evolution of dispersion over quarters; December fiscal year firms

	(1)		(2)	
	DMS Dispersion		Our Measure	
Quarter	**N**	**Mean (SE)**	**N**	**Mean (SE)**
March-May	59,890	0.29 (0.01)	9,713	1.41 (0.02)
June – August	61,175	0.25 (0.01)	9,885	1.57 (0.02)
September- November	61,102	0.19 (0.01)	9,713	1.54 (0.02)

Finally, we test to what extent the DMS dispersion measure captures the effect of public news on the consensus forecast during the month rather than a true disagreement. There are several ways to test it, which we intend to perform. We show the simplest one. When significant news arrives, we expect it to significantly affect the stock price during that month. In other words, the monthly absolute stock return can be a proxy for the arrival of significant public news. It is not a perfect proxy, as some information can affect the stock price without affecting the EPS consensus forecast, and vice versa. Still, we believe that there should be a significant correlation between the two measures.

Table 4: Mean absolute returns during the same month by quintile portfolios

Panel A: DMS measure 2010-21, December fiscal year firms.

Disagreement	**Size Quintiles**				
	S1	**S2**	**S3**	**S4**	**S5**
D1	8.0	7.4	7.1	6.1	4.8
D2	9.0	8.3	7.5	6.5	5.2
D3	10.1	9.1	7.9	7.1	5.8
D4	11.1	9.9	8.8	7.5	6.3
D5	11.4	10.5	9.6	8.3	7.4
D5-D1	3.4	3.1	2.5	2.3	2.5
t-stat	37.2	39.6	32.0	34.9	49.7

Panel B: Our measure 2010-21, December fiscal year firms.

Disagreement	**Size Quintiles**				
	S1	**S2**	**S3**	**S4**	**S5**
D1	8.5	7.5	7.0	5.9	5.3
D2	8.7	7.7	6.9	6.1	5.3
D3	9.1	8.2	7.1	6.2	5.4
D4	9.4	8.2	7.1	6.6	5.5
D5	9.5	8.3	8.0	6.8	5.7
D5-D1	1.1	0.8	1.0	0.9	0.3
t-stat	4.7	4.1	4.7	5.0	2.5

To evaluate the effect of the arrival of public news, we compute the average absolute monthly return for the DMS size/disagreement portfolios. Table 4 Panel A presents the results of this experiment for the DMS measure. The difference between the lowest and the highest disagreement quintiles in terms of the average absolute returns is very large (40%) and is highly significant (t-stats over 30). Panel B of the same table presents these statistics for our measure. While the difference between the highest and the lowest disagreement quintile is significant, its magnitude drops by 40-80%, and its significance drops dramatically. This suggests that calculating the measure of disagreement AFTER a large public information event, dramatically reduces the mismeasurement of disagreement using dispersion.

While we intend to perform robustness tests to the results presented above, it is pretty clear, that the standard measure in the literature is ill-suited to test trade-related hypotheses for two reasons: first, it measures the predictable levels of disagreement (firm and time related), which are not likely to generate new trades; and second, it mismeasures disagreement, due to biases in the dispersion stemming from the arrival of public information. Our proposed measure addresses both of these challenges, thus can be used to test trade-related hypotheses. Now we need to test whether our measure, which is based on analysts' disagreements, is a good proxy for the disagreement among investors, which drives trade.

3.3.3 Utilizing a unique data set to validate analyst-based disagreement measures.

Goetzman and Massa (2005) use retail investor data collected by Odean (1998) to run a horse race between the investors-based measures of disagreement, and the analysts-based ones, and show that the investors-based measure dominates in explaining concurrent and future returns, as well as volume. They also show that the dispersion of opinions among retail investors Granger-causes the dispersion of opinion among analysts. This work was important for our thinking, and our project complements it while being very different in three important aspects:

- We do not aim to compare the performance of alternative measures of disagreement, but rather to evaluate to what extent the analysts-based measure (in conjunction with other readily computable measures) could proxy for the investors-based measure. This is very important for many studies in which the investor data is unavailable, thus researchers must use proxies.
- Goetzman and Massa (2005) construct novel measures of investor disagreement, but use the standard measures of analysts' disagreement, which we have shown here to be ill-suited to test any trade-related hypotheses. In fact, it may well be that this is the reason for their finding that the analysts-based measures they used are predictable from past market data. We plan to run their tests to further test our measure, but the main focus is on how well it proxies for the investors' disagreement.
- Finally, we are able to connect the information observed by a retail investor, and her trading – both recorded on the same platform, which is a unique feature.

We plan to use data from TipRanks, a platform that collects and disseminates data about US equities to over half a million retail investors, mostly in the US. The data include: analysts' EPS forecasts, target prices, and buy/sell recommendations; news and bloggers' sentiment; insiders' trading; hedge funds' positions, and retail holdings and trading on the platform. Figures 1 and 2 are screenshots of the website and what investors see. The database is rather unique in allowing us to match the timing of the release of any particular information to retail investors, including changes in analyst forecasts, and the timing of the retailer investors' response - all that during the period following the earnings announcements that we use to construct our measure. We observe the time of the investors' presence on the TipRanks platform (via mobile or on the website), thus we can construct additional dynamic measures of analysts' and investors' disagreement and test them at various time windows (from one to 20 trading days). Furthermore, we observe the evolution of each investor's portfolio, the decisions to sell and buy securities, including their timing, by hundreds of thousands of paying retail investors who maintain fiat portfolios on TipRanks platform, as well as of tens of thousands of investors, who link their actual brokerage account with the platform.

While TipRanks does not have direct data on beliefs, its data on directional order flow at the individual level allows us to construct novel measures of disagreement and potentially partition them into difference of opinions and information. We can evaluate the trading behavior of a single investor over time, including the information that was made available on the platform prior to their trades. This combination allows us to create investor profiles similar to those used by Cookson and Niessner (2020). We can then build on their methodology to evaluate the degree to which each component drives volume and returns, as well as relate the two components to our measure of analyst disagreement. In addition, we can compare the behavior of investors who hold the stock and those who don't, indirectly capturing the effect of short sale constraint. Furthermore, we plan to use Goetzman and Massa (2005) methodology to test the hypotheses on the association of analysts' disagreement with the concurrent and future returns, trading volume, and short sales. These tests will include auxiliary variables that proxy for the severity of short sales constraints.

Finally, TipRanks' data augments analysts' forecasts with other sources of information made available to retail investors on the platform (see Figures 1 and 2). We plan to capture the unexpected component of the disagreement derived from all these measures – for analysts and investors alike and test their effects on trading behavior.

3.4 The Conditions for the Realization of the Research

In addition to two PIs, the team includes Prof. Ilan Guttman from NYU and Post Doc visiting scholar at NYU and Tel-Aviv University, Dr. Ruth Rooz. Our team has strong expertise in the fields of Economics, Finance and Accounting that are relevant for this project. Prof. Kandel co-authored some of the early theoretical and empirical work on the difference of opinions versus differences in information. Together with co-authors, he also developed a theoretical model of strategic manipulation of information by the management, given its interpretation by the analysts. He has extensive experience with large-scale empirical projects with multiple co-authors. Together with Prof. Guttman he published theoretical work on new types of information-based equilibria in the context of analysts' forecasts. Prof. Guttman co-authored an extensive body of theoretical work published in top Economics, Finance and Accounting journals on the interaction of firm disclosure and the analysts' forecasts. Of particular importance to this project is his work on the strategic timing of disclosure and forecasts. He also published empirical studies in top journals in Accounting on information arrival and interpretation. His expertise is crucial for the success of the project. Dr. Shaton specializes in consumer finance and worked on a variety of issues related to households' financial decision-making. Her Ph.D. work focused on the trading behavior of retail investors. Her expertise is required for our analysis of retail investors' behavior using TipRanks' data and is complementary to the other members of this team. In addition, while working as an economist at the Federal Reserve Board of Governors, she gained expertise in constructing and working with large consumer-level databases. Her published work on merging different datasets is also valuable for the construction and analysis of the datasets used in this paper. Dr. Rooz has done excellent empirical work on voluntary disclosure by firms and the ability of analysts and the market to infer relevant insights. This feeds directly into our plans to develop additional metrics of disagreement.

In the exploratory stage, we have obtained preliminary US data of analysts' forecast from IBES, as well as earnings announcements from COMPUSTAT and trading data from CRSP, for the last decade (2010-2020). Access to these databases was made possible thanks to the collaboration with Prof. Guttman and Dr. Rooz. We plan to extend the time period used in our analysis using daily market data. Next, we plan to collect data on retail investors from TipRanks. The company agreed to let us use their data for research. TipRanks is a commercial platform, thus its data is optimized for its business needs, and will require a significant effort in cleaning and characterizing the data to make it suitable for research. All the required preparation will be time-consuming.

Both the expended US data and TipRanks data analyses will require significant computing power, thus the request for the server. Furthermore, we need research assistants who are proficient in Stata and Python for data collection, preparation, and statistical analyses. More assistance will be required in the first year of the project. The statistical analyses will take place in the first two years and will require licenses for the statistical software that we use. In addition, given the size of the dataset, we will use statistical consultants to optimize our code and make it more efficient.

3.5 Expected Results and Potential Pitfalls

The first goal of our project is to propose and validate a new measure for disagreement that will overcome the shortcomings in commonly used measure (DMS). Given that our preliminary results already indicate that our measure is significantly better in capturing the relevant component of disagreement, we do not expect major pitfalls regarding this part of the project. We will perform the tests and provide new insights regardless of the nature of our results. The potential pitfall is that in the second part of the project we plan to build a new dataset utilizing data from TipRanks. The process of constructing a novel dataset with different information sources and retail investors' accounts, could take longer than expected. To alleviate this concern, we are building a working relationship with TipRanks and will start analyzing small samples of data to prepare for this project.

Figure 1. Screenshot of Amazon Stock from TipRanks (from October 29th, 2022)

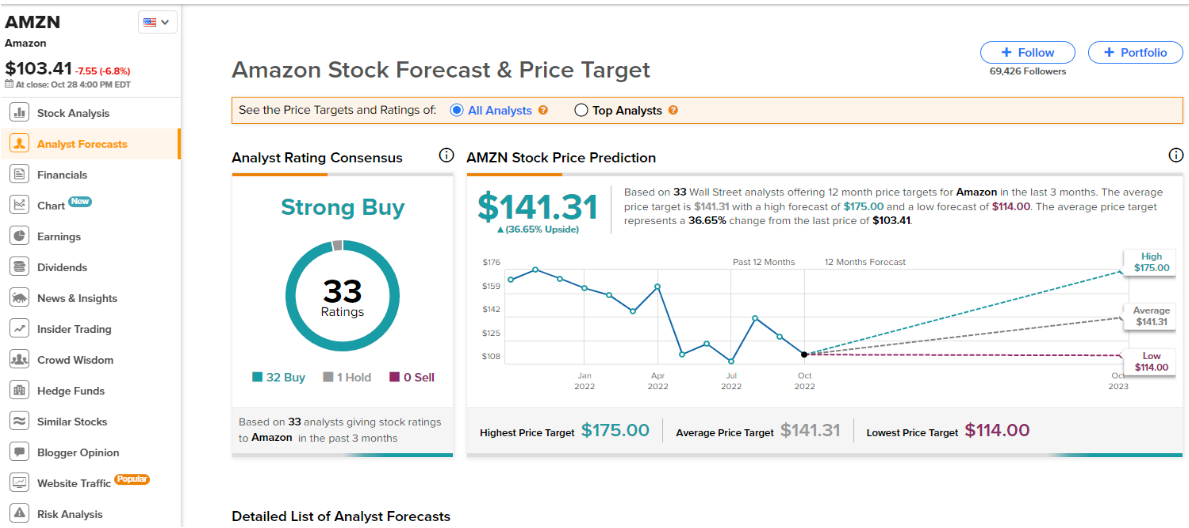
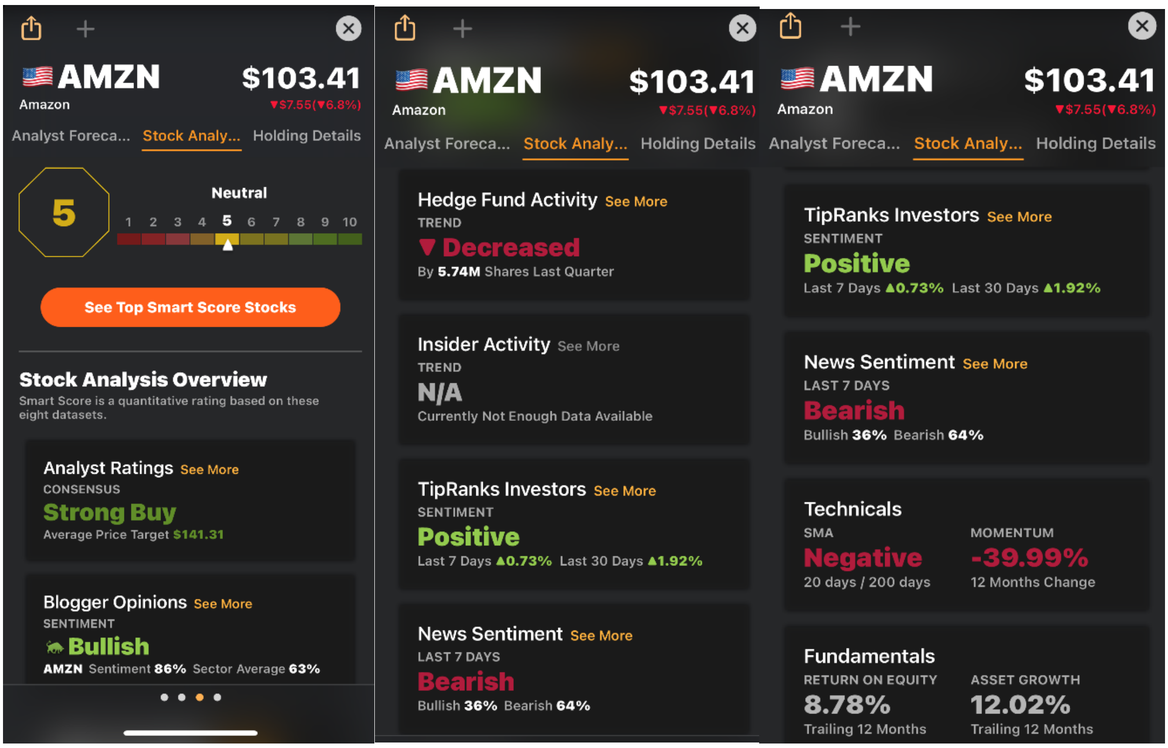


Figure 2. Screenshot of Amazon Stock from TipRanks App (from October 29th, 2022)



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