Liquidity Shocks and Arbitrageur Activity*

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Abstract

We study arbitrageur activity following temporary mispricing as a result of TV analyst recommendations using rich, intra-day trader level data. The recommendations move prices in their direction but this effect completely reverses within a week. Individual investors trade in the direction of the recommendation. Given the quick and complete reversal, trading by individual investors can be viewed as a pure liquidity shock i.e. one without any change to the fundamental value. Thus, contrarian traders can lean against the price pressure without worrying about adverse selection. Proprietary traders trade contrarian for both buy and sell recommendations. Institutional investors trade contrarian for sell recommendations, but remain neutral to buy recommendations to avoid holding overnight short positions. We also find that arbitrageurs assume less aggressive positions in difficult-to-arbitrage stocks such as illiquid stocks. Overall, our evidence points to differential limits to arbitrage faced by different types of arbitrageurs.

Key Words: Arbitrage, Emerging markets, Limits to arbitrage, Media, Stock prices

JEL Code: G14, G15

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1. Introduction

The theoretical literature on liquidity provision posits two sets of market participants that undertake this important task. First, market makers satisfy investors' demand for immediate execution of orders by taking opposite positions and holding inventories till they find other buyers/sellers. (Amihud and Mendelson, 1980, Ho and Stoll, 1981, 1983; Grossman and Miller, 1988; and Weill, 2007). Second, arbitrageurs, whose primary intent is to profit from price discrepancies, provide valuable liquidity by taking contrarian positions following a liquidity shock (Gromb and Vayanos, 2002).

In practice, both sets of market participants are likely to coexist in any market. In fact, the same market participant may play either role at different times depending on the information she has. Indeed, the possibility of taking opposite side of an informed trader – adverse selection – is an important risk in market making (Golsten and Milgrom, 1985; Kyle 1985).

If a market participant can cleanly identify a liquidity shock – i.e. deviation of price from fundamental value due to demand by uninformed investors, she would aggressively execute contrarian positions to profit from price deviation. On the other hand, if a market participant suspects an information shock – change in price due to demand by potentially informed investors, she would be less aggressive in providing liquidity via contrarian positions. Thus, the ability of the market participant to provide liquidity while minimizing adverse selection depends upon her ability to distinguish a liquidity shock from an information shock *a priori*. In many ways, the participants considered "arbitrageurs" may thus be in a better position than marker makers to provide liquidity due to their information advantage.

In this paper, we combine a clean liquidity shock with rich trade-level data that identifies various categories of market participants to provide evidence of the above phenomenon.

A simple way to identify liquidity shock is to use an event that is known to cause temporary price fluctuations and then, examine (i) when prices revert; (ii) who trades in the direction of shock (noise traders) and who trades contrarian (the arbitrageurs); and (iii) what (if any) constraints the arbitrageurs face. Existing research on the effect of media recommendations on stock prices shows that such recommendations may lead to temporary mispricing in a stock. For example, Engelberg, Sasseville, and Williams (2012) find that following buy recommendations on a TV program called "Mad Money", stocks experience large overnight returns that subsequently reverse over the next few months.[1] Such temporary mispricing created by TV analyst recommendations, therefore, provides an ideal setting to examine liquidity provision by arbitrageurs.

We use unique, hand-collected data from July 2009 to June 2010 for a TV program called "CNBC Awaaz Stock 20/20" that recommends stocks to buy and sell on every trading day. A key aspect of the program is that it is *aired before stock markets open for trading*. As we explain in detail in Section 4.1, this empirical setting enables us to study the arbitrageur activity carefully. Because the recommendations are aired before markets open for the day, studying the trading activity in the first half hour enables us to sharply identify a liquidity shock. If the recommendations were aired when the markets are already open, any buying or selling activity by investors *before* the recommendation may be because of firm-specific information filtering in about the stock that is going to be recommended. Such a leakage of firm-specific information may also affect the likelihood of the recommendation itself. If trading activity *after* the

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[1] Bolster and Trahan (2008) and Hartley and Olson (2016) provide further evidence on the "Mad Money" effect.

recommendation captures any remnants of the effect of firm-specific (fundamental) information, we may not be able to isolate the transient effects of the liquidity shock caused by the recommendation, per se. In other words, we require a clean liquidity shock to make inferences about liquidity provision.

We augment the data on recommendations with data on stock prices and intraday trading behavior of various market participants. To start with, we examine our basic assumption that media recommendations indeed lead to temporary mispricing. For this purpose, as a first step, we examine the criteria that determine which stocks are selected for a buy or sell recommendation among the population of listed stocks. We use a conditional logistic model where the outcome on a particular day is either a buy recommendation or a sell recommendation compared to a reference group of stocks without a recommendation. In this step, we find that stocks that have performed well the previous day are significantly more likely to be recommended as buys while stocks that have performed poorly the previous day are more likely to be recommended as sells.

In the second step, we generate a group of control stocks by matching on the propensity scores derived from the logistic model. Then, we compare the performance of stocks that are recommended as buy/sell before trading opens for the day (treatment stocks) to a set of stocks that are similar on all selection criteria but did not get recommended (control stocks).

To estimate the abnormal stock returns for both treatment and control stocks, we use the characteristics-based methodology of Daniel, Grinblatt, Titman, and Wermers (1997) – henceforth DGTW. Since the recommendations are made before trading opens for the day, we examine the announcement effect of a recommendation using the closing price on the day before the recommendation and the opening price on the day of the recommendation. We find that the stock opens 100 basis points (bps) higher than a control stock on a buy recommendation and 82

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bps lower than a control stock on a sell recommendation. However, prices start reverting the same day. Stocks that received a buy recommendation fall by 17 bps from open to close. Conversely, stocks that received a sell recommendation rise by 30 bps from open to close. Thus, we confirm that in our setting media announcements do create temporary mispricing in stocks and that a part of the mispricing reverses itself by the end of the same day.

Next, using a calendar-time portfolio approach, we examine if this pattern of stock price reversal continues beyond the close on Day 0. Using raw returns, DGTW-adjusted returns, and a four-factor-alpha based on the model in Carhart (1997), we find that stock prices revert to their fundamentals within a week of the recommendation.

When examining the intraday price patterns, we find that a stock that receives a buy recommendation appreciates by over 40 bps in the first half hour of trading; in each of the other half-hour trading intervals, the stock either falls or trades flat. In contrast, a stock that receives a sell recommendation falls by about 10 bps in the first half hour of trading; in each of the other half-hour trading intervals, the stock either trades flat or appreciates. This price movement in the first half hour of trading represents noise trading that pushes the price further in the direction of the recommendation.

After documenting the price shock and eventual reversal, we analyze trading activity and trading profits to identify the arbitrageurs and study the pattern of their activity. Using unique high-frequency data on the type of the participants that trade on the Bombay Stock Exchange (BSE), we compare intraday net buying, defined as the buy minus sell order imbalance, on the day of the stock recommendation for the treatment stocks to that of the control stocks. In particular, we characterize trading patterns of three types of investors – individual, institutional and brokers trading on their own account (hereafter proprietary traders). An important theme in

the literature on the limits to arbitrage is that arbitrageurs are sophisticated traders, better able to identify mispricing than other, less sophisticated investors (Gromb and Vayanos, 2010). In general, institutional investors are considered informed/sophisticated.[2] As Barber and Odean (2013) highlight, individual investors are more likely to be unsophisticated. Proprietary traders, who typically have significant experience of trading in the markets, are also likely to be sophisticated. This plausible information advantage of institutional investors and proprietary traders may help them distinguish an information shock from a liquidity shock.

In the first half hour of trading, individual investors trade significantly in the direction of the recommendation. In contrast in that same period, proprietary traders are significant contrarians: they sell the stocks recommended as "buys" and buy the stocks recommended as "sells". During the remaining part of the day, proprietary traders close the contrarian positions they assumed in the first half hour. Institutional investors behave differently; they trade contrarian in the first half-hour only when the stock is recommended as a sell. Further, they don't close their positions by the end of the day, carrying them forward almost entirely. Institutional investors view buy recommendations with greater caution. Trading contrarian following a buy recommendation involves taking a short position. While the Securities and Exchange Board of India (SEBI) allows institutional investors to take short positions, it does not allow them to square-off their transactions intra-day.[3] Carrying a short position overnight is more difficult, compared to just assuming it intra-day because it requires borrowing the stock, as SEBI does not

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[2] For example, studies by Hensershott et al (2015), Boulatov et al. (2013), Griffin et al. (2012), Busse, Green and Jegadeesh (2012), Jegadeesh and Tang (2010), Campbell et al. (2009), Irvine et al. (2007), among others, conclude that institutional investors are informed. Boehmer and Kelley (2009) and Sias and Starks (1997) provide evidence that institutional investors improve price efficiency. Not everybody agrees. Lewellen (2011) finds that institutional investors are uninformed. Brunnermeier and Nagel (2004) show that even though hedge funds were informed about overvaluation about the technology stocks they chose to ride the bubble rather than trade against the mispricing.

[3] Annexure I to SEBI circular MRD/DoP/SE/Dep/Cir- 14 /2007 dated December 20, 2007.

allow naked short positions. Therefore, institutional investors face greater difficulties in shorting than proprietary traders and do not arbitrage following buy recommendations. However, institutional investors do not face such difficulties when buying a stock following sell recommendations. Consistent with this hypothesis, we find that for stocks recommended as a sell, net buying by institutional investors is about 10 times that by proprietary traders. On the other hand, institutional investors trade much less than proprietary traders when selling a stock following a buy recommendation.

We then find that proprietary traders and institutional investors indeed make money through their contrarian positions. Following the buy recommendations, the most aggressive contrarian proprietary traders make an extra profit of about INR 18,000 in treatment stocks over and above that in control stocks. The most aggressive contrarian institutional investors make an extra profit of about INR 0.65 million on average following a sell recommendation. In all these cases, the profits of the most aggressive contrarian traders are significantly larger than the least aggressive ones.

Interestingly, even though proprietary traders buy on average following sell recommendations, most aggressive buyers among them don't make significant extra profits compared to most aggressive sellers. It seems that following sell recommendations, proprietary traders face competition from more aggressive institutional investors, who scoop up the profitable trades. These results shed light on the competition between proprietary traders and institutional investors as liquidity providers in our setting.

Finally, we examine the frictions that affect the process of arbitrage. Following Pontiff (2006) and Gromb and Vayanos (2010), we hypothesize that the positions taken by arbitrageurs would be smaller when frictions preventing arbitrage are greater. Accordingly, we sort stocks on

liquidity and find that both proprietary traders and institutional investors assume significantly smaller contrarian positions in illiquid stocks. Together with the evidence described above that institutional investors do not play the role of arbitrageurs following a buy recommendation, we infer that short sale constraints and lack of liquidity represent the key factors that limit arbitrageur activity in our setting.

To our knowledge, ours is the first study to use rich, trader-level data to identify the arbitrageurs and examine *differential limits to arbitrage across different types of investors*. We highlight the role played by proprietary traders trading on their own account as arbitrageurs. Given the short sale constraints on institutional investors, we show that proprietary traders play a critical role in leaning against the price pressure following a liquidity shock. Our results on proprietary traders complement those in Biais, Declerck, and Moinas (2016). Using data from Euronext and the French financial markets regulator, they find that proprietary traders provide liquidity. Our study focuses on a clean liquidity shock and compares the behavior of institutional investors and proprietary traders. We find that these two kinds of traders are affected by differential constraints and hence act as liquidity providers in different situations. We also find that when both of them can be contrarians, their competition has implications for profitability of their trades.

Ours is also the first investigation of arbitrageur activity in an emerging market. Previously documented evidence of limits to arbitrage has been limited to the developed markets. But emerging markets may provide richer settings to examine these limits. On the one hand, pricing anomalies can persist because regulations restrict hedge funds, which can execute long-short strategies to arbitrage away any pricing anomalies. Further, individual investors – typically considered noise traders - may participate more intensively in emerging equity markets than they

do in the developed markets.[4] Thus, noise trader risk faced by arbitrageurs – as modeled in De Long, Shleifer, Summers, and Waldmann (1990) – may be also be greater in emerging markets, rendering arbitrage more difficult. On the other hand, as Black (1986) argues, it is beneficial to have noise traders as they increase depth and liquidity in the financial markets, which may make arbitrage easier. Therefore, examining arbitrageur activity in an emerging market is likely to uncover patterns that may enrich our understanding about how arbitrage forces work in general. Given the importance of "correct" prices in the financial markets for capital allocation, researchers and policymakers should care at least as much about the arbitrage activity in emerging countries as they do in developed countries.

Though the study focuses on India, for several reasons, our findings have wider relevance. First, India is English-speaking and has English legal origin (La Porta et al. (1998)). Thus, its legal institutions are similar to those in other English legal origin countries. Second, India is the largest democracy in the world and the fourth estate in India enjoys freedom greater than many other emerging economies. For example, 2015 Freedom of the Press report by the Freedom House ranks India ahead of Brazil, China, Hong Kong, Mexico, and Russia.[5] Finally, as Indian accounting and financial data is generally of good quality, recent studies have used the Indian context to examine other issues in finance (for example, see Visaria (2009); Lilienfeld-Toal et al. (2012); Vig (2013); Banerjee and Duflo (2014); Gopalan et al. (2014)).

Next we describe the institutional details of the TV program.

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[4] For example, in Taiwan about 90% of trading in equities is by individuals (See Barber et al, 2009). In India, the fraction is about 50% (http://www.financialexpress.com/article/markets/indian-markets/cy15-retail-turnover-in-cash-markets-grows-15-on-year/). In the U.S., retail investor volume is just 2% of NYSE volume as noted by Evans (2009).

[5] https://freedomhouse.org/report/freedom-press-2015/2015-press-freedom-rankings.

2. Institutional Background

2.1. CNBC in India

Network18 (through its subsidiary TV18) operates one of India's most popular television broadcasting networks comprising of numerous news, business news and regional language entertainment channels. In 2005, in collaboration with CNBC, it launched CNBC Awaaz, which is India's No. 1 regional language (Hindi) business news television channel with approximately 60 percent share of viewership.

From its launch in 2005, CNBC Awaaz rapidly built up a reputation for providing innovative programs in a viewer-friendly dissemination of information, analysis and actionable suggestions. An indication of the viewership of CNBC Awaaz is provided by the viewership of its budget coverage in 2010 (a period relevant for our study), which had almost 4 times the viewers of its nearest competitor.[6]

Sanjay Pugalia, Editor, CNBC Awaaz has described its unique selling point as follows: "The consumer channel is primarily targeted at small investors. It is first and foremost for those viewers or consumers who are earning some money, saving some and need proper advice to invest. The channel has been principally designed in the manner wherein experts provide inputs in a manner that will help consumers take their own decisions on all the possible ways he / she can save or make money."[7]

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[6] Source: TAM Media Research, which measures TV audience in India.
[7] http://www.indiantelevision.com/interviews/y2k6/executive/sanjay_pugalia.htm

Over the five year period between 2005 and 2010, viewership of business news in India rose from 10 million to 55 million.[8] It is widely believed that regional business news channels such as CNBC Awaaz played an instrumental role in this growth story.

2.2. Stock 20/20

In 2009, CNBC Awaaz began airing an innovative daily program titled "Stock 20/20" in the morning, before the opening of the daily trading session. The show features stock recommendations made by a panel of four experts based on their anticipation of performance of the stock for that specific trading day. Each expert picks ten stocks, thus providing the viewer with 40 stock recommendations for each trading day. Later in the day (after market-closure), the intraday performance of these stocks are assessed in a separate show aired at 3:30 p.m.

In keeping with the spirit of the time, the show was modelled on the 20/20 cricket game that is immensely popular in India. The name 20/20 refers to the fact that each team gets to play exactly one innings consisting of pre-defined number of deliveries (equivalent to pitches in baseball terminology). The number of deliveries is restricted to 20 overs with each over consisting of six pitches.

The Stock 20/20 show revolves around stock picks made by a panel of four experts. The program is fast-paced, with the experts individually making their stock picks in the form of either a buy recommendation (referred to as a batsman) or a sell recommendation (referred to as a bowler – equivalent to a pitcher in baseball). Such terminology is probably driven by the desire to maintain parallels with a 20/20 cricket game.

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[8] Based on TAM Media Research findings, http://www.indiandth.in/Thread-CNBC-Awaaz-completes-five-years-of-success.

The background music as well as the racy pace of the Stock 20/20 show mirrors a typical 20/20 game of cricket, in that it aims to keep the viewer engaged as well as entertained. To reel off 40 stocks in one hour necessarily requires the experts to make quick and categorical calls. The format of the program requires them to give the broad punchlines rather the details of the logic underlying their analysis. Mr. Neel Chowdhury, VP, Marketing, CNBC-TV18 and CNBC Awaaz reflects this school of thought: "We at CNBC-TV18 and CNBC Awaaz are always looking for ways to make our programming more and more tailored to our viewers' preferences. We realized that many of our viewers, especially the day traders, prefer hard-core suggestions while stock analysis, even though important, is secondary. 'Stocks 20/20' will make the process of guiding the investors more direct at the same time adding an innovative angle to the process."[9]

3. Data and Sample

In this section, we describe the data on recommendations, daily stock prices and volumes, stock characteristics, and intra-day prices and trading.

3.1. Data on stock recommendations in Stock 20/20

To collect our sample, we examined video footage of the Stock 20/20 show spanning a year (July 1, 2009 to June 30, 2010). Our sample dataset was created by manually recording the 10 stocks picked by each of the four experts. Each expert may nominate any number of batsman (buy recommendations) or bowlers (sell recommendations). On average, the experts tended to pick more batsmen than bowlers by a factor of about 4 is to 1.

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[9] See "20/20 fever now on CNBC Awaaz", Media News Mumbai, April 03, 2009.

3.2. Data on stock returns

The selected stocks were matched on the basis of the ticker symbol with the stock prices and financial statement data obtained from the Prowess database maintained by the Centre for Monitoring the Indian Economy (CMIE). This database has been used by many recent studies on the Indian financial sector.[10] The final sample consists of 6,225 stock picks (5,036 buy and 1,189 sell recommendations) over 250 different trading days.

Table 1 presents descriptive statistics using daily data between July 1, 2009 and June 30, 2010 for all stocks listed on the BSE. The table is based on a stock-day panel, where on each day a stock may receive a buy or a sell recommendation. This is the universe from which Stock 20/20 chooses its stock picks. Panel A shows explanatory variables that are later used to identify propensity-score matched control stocks for each stock picked on the TV program. The average lagged daily raw return is 12 bps. The average raw return from Week –1 to Day –2 is 37 bps, that from Month –1 to Week –1 is 2 percent, and that from Month –6 to Month –1 is 27 percent. The average daily market capitalization is Rs. 12.8 billion and the book-to-market ratio is 1.46. We find that individual investors on average hold 32.86 percent of a BSE-listed company and that 1 percent of the companies in our sample are either in the SENSEX or Nifty.[11] Over three-fourth of the companies do not have any analyst following but on average a little over one analyst follows a company.

In Panel B of Table 1, we report both the raw returns as well as benchmark-adjusted returns. Benchmark-adjusted returns are characteristic-adjusted returns, based on market

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[10] For example, see Banerjee and Duflo (2014), Lilienfeld-Toal et al. (2012), Vig (2013), and Gopalan et al. (2014) among many others.
[11] The SENSEX is the main index published by the BSE and consists of 30 stocks. The Nifty is the main stock market index published by the National Stock Exchange of India consists of 50 stocks.

capitalization, market-to-book ratio, and one-year prior returns, as described in DGTW. The characteristic-adjusted returns appear economically small for various forward-looking windows. This makes sense since Table 1 is for the entire universe of stocks and we do not expect to find non-zero abnormal returns for the whole universe.

3.3. Data on intra-day prices and trading behavior

In addition to the data on stock recommendations, returns and stock characteristics, we use intraday order and trade data from the BSE to examine the trading patterns around the recommendations. The dataset has all orders and trades from July 1, 2009 through June 30, 2010. The order book dataset includes the BSE scrip code, date, time of order, type of order (limit, market, etc.), whether it is a buy or a sell, the limit price of the order, the displayed as well as the total order size, whether the record is an order addition, modification, or deletion, a proprietary trader code, a client account number, a trader category, and a unique order number. The trade data includes the BSE scrip code, date, time of trade, the order numbers of the buy and sell orders involved in the trade, the trade price, and the trade size. The unique order number helps us match the order data to the trade data.

We sign every trade as buyer- or seller-initiated in the following way. For both orders involved in a trade, we identify all the records from the order data with a time stamp prior to the trade time. We include order modifications also in this set of records. From a chronological sort of these records for each order, we pick the last record. This gives us two records, one each for the buy order and the sell order involved in the trade. Across these two records, the one with the time stamp closer to the trade time is the one that triggers the trade and hence the trade is signed with the sign (buy/sell) of this order.

The data also assigns traders to a large number of different categories. We combine these into three broad categories – individual investors, institutional investors and others. Table 2 presents the mapping of original trader categories to our broad categories. In addition to these three trader categories, we create a fourth category called proprietary traders. This category is for brokers who trade on their own account. Their orders are identified in the data with a client account number of "OWN".

The order imbalance for each trader category over each half-hour or over each day is the total value bought minus the total value sold using the sign of the trade-triggering orders by all traders in that category during that time interval. We also calculate the trade imbalance over each trading interval for each trader category as the total value bought minus the total value sold using both all orders during that time interval.

Using the data on trading and prices we also calculate profits or losses made by different categories of investors the day of the recommendation.

4. Price Patterns around Recommendations

Recent literature has examined the role of media in influencing asset prices. The findings are interesting and diverse. Media coverage could either be a source of firm-specific information (Chan (2003), Tetlock, Saar-Tsechansky, and Macskassy (2008)) or a reflection of market sentiment (Tetlock (2007)). At the same time, media coverage could also channelize investor attention (Fang and Peress (2009)), thereby lowering the cost of capital (Merton (1987)). Other important studies that aim to unravel the role of media in asset price formation include Soltes (2008), Gurun and Butler (2010), Engelberg and Parsons (2011), and Solomon, Soltes, and Sosyura (2011).

4.1. A Clean Empirical Setting To Identify Liquidity Shock

In this study, we use TV analyst recommendations to identify a clean liquidity shock. The Stock 20/20 program offers a unique setting for examining this question. However, before we go on to examine behavior of arbitrageurs in response to this shock, first we have to establish that in our setting the recommendations truly result in trading behavior unrelated to the fundamental value. To do this we examine see if the recommendations have any lasting effect on the stock price.

The standard time slot for the Stock 20/20 show is in the morning before the beginning of the day's trading session. This provides a clean empirical setting to study the process of reaction of price to recommendation. The experts' recommendations are made just prior to the opening of the day's trading session and the information about the recommendations is already in the public domain when the markets open for trading. Thus, the recommending analysts have weak incentives to leak any information to their preferred customers.[12]

To test the efficient market hypothesis, some studies of the U.S. markets examine stock recommendations made by TV analysts while markets are open. For example, Busse and Green (2002) examine the Morning Call and Midday Call segments on CNBC TV in the U.S, both of which occur during the market trading hours. "Mad Money", the TV program in the study by Engelberg, Sasseville, and Williams (2012) airs at 6 PM, after the regular market hours but while the after-hours market is still open. Barclay and Hendershott (2003) find non-trivial trading volume in the after-hours market. Therefore, in settings where the recommendations are made while markets are open, information may leak out. This may happen partly because the

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[12] Beneish (1991) provides a lengthier discussion of the incentives of analysts to provide information to financial reporters ahead of their customers.

recommending analysts may have incentives to provide information to their favored clients ahead of the public recommendation.

Our setting also allows us to identify the price reversal/continuation correctly. For example, if the program were aired after the markets have already opened for trading, a stock to be recommended as a buy may appreciate in price before the recommendation becomes public. In that case, it would be unclear whether that positive return after the market opening (but before the recommendation) was the cause or the consequence of the buy recommendation. This lack of clarity may lead to under- or over-estimation of the announcement effect of recommendations. If information leaks, the price appreciation before the announcement should be included in calculation of the announcement effect. Otherwise, it should not be. Our clean setting is of great advantage since it enables us to correctly measure the announcement effect of recommendations, which is crucial. If we under- or over-estimate the announcement effect, we may draw incorrect inferences about whether there is any lasting effect of recommendations.

4.2. Dissecting Analyst Recommendations

To begin, we want to understand which stocks receive buy or sell recommendations. This serves two purposes. First, we throw light on the reasons why the analysts pick certain stocks – to provide information to investors or to ride on the wave of attention the stock is already grabbing. Second, more importantly, we want create a control sample of stocks that could have received a recommendation, based on observable factors, but did not. Then we can compare the price pattern of stocks that were recommended to the price patterns of these control stocks. For this purpose, we estimate a conditional logit to determine the likelihood of a stock receiving a buy or a sell recommendation on any given trading day. We use the variables in Panel A of Table 1 as our explanatory variables for the logit model along with an interaction between prior volume

and the number of analysts following the stock. The dependent variable in each regression is the indicator that a stock received a recommendation. We estimate separate logit models for buy and sell recommendations.

The estimates as well as the marginal probabilities are presented in Table 3. We find that the prior day's return is an important determinant of whether the TV analysts pick a stock. Specifically, we find that if the previous day's return is higher by one percentage point, the likelihood of a buy recommendation goes up by 2.1 percent and likelihood of a sell recommendation goes down by 3.1 percent. This shows that the TV analysts base their decision to select a stock on the stock's most recent performance. They make buy recommendations for recent winners and sell recommendations for recent losers.

Abnormal volume on the previous day also plays an important role. Higher abnormal volume increases the likelihood of both buy and sell recommendations. Barber and Odean (2008) define attention-grabbing stocks as those that have high abnormal trading volume and extreme one-day returns among other things. As described in section 2.2, the TV analysts' target audience is individual investors. The return and the volume results in Table 3 are consistent with the analysts recommending stocks that have already caught the individual investors' attention.

Two other significant explanatory variables are the number of analysts and the average trading volume over the six-month period prior to the one month before the recommendation. We include these variables as proxies for overall information availability for a stock. Greater analyst coverage and overall higher trading means it is likely that more information gets incorporated in the stock price on a regular basis. If the TV analysts' objective is to provide information about stocks for which less information is available, we should expect a negative effect of analyst coverage and average trading volume on the likelihood of recommendations. In

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fact, we find the opposite results. Analysts are more likely to give both buy and sell recommendations to stocks that have higher analyst coverage and trade more. Thus, the TV analysts seem to select stocks not to provide more information about them but those that have already caught the attention of individual investors.

We find that the interaction between analyst coverage and the five-month average trading volume is negative for both buy and sell recommendations (although significant only for buys). This means that, to some extent analyst coverage and trading volume are substitutes. An additional analyst does not have as much impact when the stock is highly traded as when the stock does not trade much.

We use the explanatory variables from the logit model to identify propensity-score matched control firms for the treatment firms. Table 4 shows the distribution of propensity score differences for each pair of treatment and control firms. The mean and the median differences in propensity scores for buys and sells are quite small. Even the 99th percentile is in the range of 0.0007 to 0.0017 indicating that the treatment and control stocks are quite well-matched.

4.3. Daily Returns to buy and sell recommendations

Now, we examine the returns on the stocks that received buy and sell recommendations. Table 5 presents mean difference in raw returns and DGTW-adjusted returns between the treatment and control stocks. First, we examine the return difference for the day before the recommendation. For neither buy nor sell recommendations, this difference is statistically significant. This is not surprising since previous day's return is one of the variables in the logit model used to select the propensity score matched control stocks. This result just emphasizes that the treatment and the control stocks are well matched on this specific dimension as well.

The critical question is what happens after the recommendation. We want to know whether the picks by the TV analysts have any announcement effect on prices and if yes, whether the effect is permanent or transitory. To answer this question, we look at the return from close of the previous day to the opening price on day 0 – the day of the recommendation.[13] This return captures the pure announcement effect of the stock being recommended by the TV analysts. As discussed in Section 4.1, given the timing of the show, all the information generated by the TV analysts recommending the stock is publicly available when the market opens on day 0. We find that a statistically significant positive abnormal characteristic-adjusted overnight return of 100 bps accrues to the stocks with buy recommendations. The overnight abnormal characteristic-adjusted return for sell recommendations is negative 82 bps. Thus, there is a significant announcement effect. This result is similar to the findings in the U.S. market that prices react very quickly to analyst recommendations – for example as documented by Busse and Green (2002) and Engelberg, Sasseville, and Williams (2012).

However, the strong announcement effect on prices turns out to be quite temporary. On day 0 itself prices start reverting – the day 0 open to close abnormal return for buy recommendations is negative 17 bps and for sell recommendations it is 30 bps, both statistically significant at the 1 percent level. The overall abnormal return from day -1 close to day 0 close is still significantly positive for buys and significantly negative for sells. But if investors followed the recommendations and bought or sold after the market opened, they would incur losses on both types of recommendations.

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[13] Note that the number of treatment and control firms are different because a control firm may be a control firm for more than one treatment firm.

Figure 1 shows the cumulative abnormal returns (DGTW-adjusted) for the treatment group minus the control group from day -1 to day 5. It shows the spike up on day 0 open and reversal by close on day 0. It also shows that the reversal continues until day 5. To examine the return pattern over longer horizons we adopt the calendar-time portfolio approach. A calendar-time portfolio with a holding period of n days, is long in the stocks recommended within the previous n days and short in the matched control stocks. We can think of the daily return on the n-day calendar time portfolio as the average of daily returns for the first n days after the recommendations. Table 6 shows the average daily returns on the calendar-time portfolios for various holding periods up to 1 year. We show raw returns, DGTW-adjusted returns as well as alphas for the Fama-French-Carhart four-factor model. CMIE calculates the market, SMB, HML and momentum factors for the Indian market.[14] The set of columns on the left show the calendar-time portfolio returns, including the announcement effect on day 0. We see that for buy recommendations in Panel A, the initial effect completely disappears by the end of the first week. For sell recommendations in Panel B, the effect lingers a little longer but not much longer.

Figure 2 shows the calendar-time portfolio returns, including the announcement effect. It visually confirms the initial spike and very quick reversal. For both buy and sell recommendations, the reversal happens in less than 10 days. After the reversal, there does not seem to be any price movement.

Figure 3 as well as the set of columns on the right in Table 6 show the return on the calendar-time portfolios, excluding the announcement effect – i.e. the long and short positions are taken at the opening price on day 0 and thus the returns exclude the spike between day -1

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[14] The factors are available at http://www.iimahd.ernet.in/~iffm/Indian-Fama-French-Momentum/. Agarwalla, Jacob, and Varma (2013) describe the detailed methodology.

close and day 0 open. This captures the actual return earned by investors who follow the recommendations. We see that this return is robustly negative and stays negative for more than three months for buy recommendations. For sell recommendations, while the initial return starting from day 0 open is positive and significant, it does not remain so as the subsequent returns turn out to be quite noisy.

To summarize, there is a positive announcement effect following buy recommendation but its starts to revert immediately and completely disappears in about a week. Similarly, sell recommendations experience a negative announcement effect and a quick reversal. Thus, the effect is consistent with media creating temporary mispricing in stocks. In our setting, the recommendations do not result in any permanent effect on prices. Thus, we can use any trading in this setting as a clean liquidity shock without any information about the fundamental value.

Next, we attempt to understand the trading pattern of different types of investors following the recommendations.

5. Noise Traders and Arbitrageurs

Since the prices start reverting on day 0 itself, we look at the intra-day returns and trading patterns on day 0 to better understand the forces of arbitrage. Our setting allows us to study the intra-day trading patterns by various categories of investors. Because the recommendations are aired before markets open for the day, studying the trading in the first half hour enables us to sharply identify noise trading and arbitrage activity.

5.1. Intra-day returns and profit opportunities

In Section 4, we already presented evidence that following a buy (sell) recommendation the opening price is higher (lower) than the closing price the previous day. Figure 4 shows a plot

of the returns for the treatment firms relative to control firms for every half-hour from the time the market opens for trading.[15] For buy recommendations, during the first half-hour the price moves higher by more than 40 bps compared to the already high opening price – a statistically significant effect. In a similar vein, the first half-hour return for sell recommendations is a statistically significant negative 10 bps. After the first half-hour though, the price trend reverses and returns are generally negative for buy recommendations and positive for sell recommendations.

This relatively quick correction in price trends implies that the window for maximizing profits from (following up on) CNBC analyst recommendations is rather small. Since the deviation from the "true" price is greatest at the end of the first half-hour, to maximize profits one must create contrarian positions (sell positions for buy recommendations and buy positions for sell recommendations) by the end of the first half an hour of trading. Delaying the creation of the positions beyond the first half-hour would erode the profit potential as arbitrageurs would lose out on capturing part of the correction.

5.2. Order Imbalance by Trader Type

The price patterns suggest that contrarian trading upon announcement of buy (sell) recommendations can provide profitable trading opportunities. The BSE dataset allows us to examine whether there are traders who deploy this strategy. The dataset provides information on

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[15] Effective January 4, 2010, the BSE extended its trading hours by opening earlier at 9:00 am rather than 9:55 am. It continues to close at 3:30 pm. Since there are more half-hours after the extension in trading hours, we align the half-hours at market open. Thus, for dates prior to January 4, 2010, the market closed after half-hour interval 11, whereas for those dates after January 4, 2010, the market closed after half-hour interval 13.

orders placed by individual investors (or retail investors), institutional investors and proprietary trades made by brokers.[16]

Given that the CNBC Awaaz Stock 20/20 program is targeted at individual investors, we would expect them to trade in the direction of the recommendation. On the other hand, sophisticated investors like institutions and proprietary traders are likely to be contrarians. We determine the order imbalance in each half-hour for each category of trader by taking the difference in traded value between buyer-initiated trades and seller-initiated trades. Figures 5-7 plot the half-hour order imbalances for treatment stocks minus those for control stocks. Figure 5 shows the plot for individual investors while Figures 6 and 7 show the same for institutional investors and proprietary traders, respectively. The plots on the left are based on order imbalance calculated using all executed market orders submitted by the particular type of trader and the ones on the right are based on trade imbalance calculated using all executed orders submitted by the particular trader category.

5.2.1. *Response to Buy Recommendations*

For ease of exposition, we consider the response to buy recommendations first. Consistent with the expectations, Figure 5 (Panel A) shows that individual investors trade in the direction of the buy recommendations during the first half-hour. The left half of Panel A indicates an order imbalance in market orders (i.e., market buy orders less market sell orders) of INR 1.5 million. The imbalance in total orders is also significant, amounting to INR 2.5 million in the first half-hour. This trading pattern combined with the price pattern discussed in the previous sub-section, make it evident that individual investors are exerting price pressure on the

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[16] We ignore the fourth trader category called "others" as their trading behavior and motivation are unknown.

market through buy orders. In contrast, institutional investors seem to ignore the buy recommendations; their order imbalance in both market orders and limit orders are close to 0 for buy recommendations, as can be seen in Figure 6, Panel A. The combined order flow imbalance of individual investors and institutional investors requires someone to take a contrarian position in order clear markets. The evidence in Figure 7 (Panel A) is unambiguous. Proprietary traders use both market order and limit orders to take a contrarian position of selling in a market that is experiencing buying pressure, in the process supplying liquidity. The picture that emerges in the first half of trading is clear. Individual investors trade in the direction of the recommendation. Institutional investors remain largely neutral, but proprietary traders take contrarian positions.

Figure 8 plots trade imbalances aggregated at the daily level for institutional investors and proprietary traders. Looking at Panel A, for buy recommendations, we see that for day 0, the proprietary traders have on an average negative trade imbalance of INR 630,000. This is about half the trade imbalance of INR -1.2 million at the end of first half-hour as shown in Figure 7. Thus proprietary traders seem to be closing a lot of their positions that they established at the beginning of the day.

5.2.2. *Response to Sell Recommendations*

Panel B in Figures 5, 6, and 7 shows the half-hourly order imbalance of individual investors, institutional investors, and proprietary traders in response to sell recommendations. Individual investors are selling in the first hour using market orders, but buying using limit orders. Upon aggregating both market and limit orders (right figure in Panel B of Figure 5), we find that individual investors are not taking significant positions in either direction. This tepid response is in stark contrast to how they react to buy recommendations. This reaction is not surprising since individual investors have to short sell stocks if they wish to follow a sell

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recommendation, which may be difficult for them.[17] On the other hand, arbitrageurs, who have to assume contrarian positions (i.e., place buy orders following a sell recommendation) do not face any short sales constraints. Figures 6 and 7 show that both proprietary traders and institutional investors assume contrarian buy positions in the first half-hour of trading.

Looking at daily trade imbalances for sell recommendations in Panel B of Figure 8, we see that institutional investors have a positive trade imbalance of INR 8.8 million for day 0. This is very close to their trade imbalance at the end of first half-hour of INR 9 million as seen from Figure 6. The institutional investors don't seem to be closing their positions at the end of the day. Contrast this with the proprietary traders' trade imbalance, which goes down from about INR 1.1 million at the end of first half-hour to only about INR 330,000. Again, as in the case of buy recommendations, proprietary traders appear to be closing their contrarian positions by the end of the day.

5.2.3. Summary of response to recommendations

The evidence presented above paints a very clear picture. Individual investors create temporary price pressure in the first half-hour by trading in the direction of the recommendation. Only proprietary traders assume contrarian arbitrage positions for buy recommendations. However, both proprietary traders and institutional investors assume contrarian arbitrage positions for sell recommendations. By trading opposite to the price pressure, the contrarian traders provide liquidity following the recommendations. They "lean against the wind" to use the terminology in Weill (2007). In this case, the arbitrageurs – the sophisticated investors – can

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[17] In Indian markets, investors can take an intraday short position without having to borrow a stock as long as they square the positions by the end of the day. However, knowledge about this possibility may require certain sophistication which the individual investors following the recommendation may not have.

safely trade against the price pressure knowing that this is not an information shock but a pure liquidity shock.

The difference in response of institutional investors and proprietary traders is, at first glance, surprising. Institutional investors are sophisticated investors and one would expect these traders to assume contrarian positions to take advantage of the impending price correction. However, institutional investors are at a slight disadvantage to proprietary traders on two counts. First, proprietary traders have superior access to information about market conditions (e.g., the proclivity of individual investors to respond to buy recommendations) because they are directly observing order flow due to the nature of their activities. Second, responding to a buy recommendation using a contrarian strategy involves shorting the stock. The institutional investors face more short sale constraints. The Securities and Exchange Board of India (SEBI) allows institutions to take short positions, but it does not allow them to square-off intra-day positions. (See Annexure I to SEBI circular MRD/DoP/SE/Dep/Cir- 14 /2007 dated December 20, 2007 for details). This restriction is consistent with institutional investors' tendency to carry overnight positions as seen from Figure 8. Squaring a short position by the end of the day is easier than carrying it overnight because the former does not require borrowing a stock. Thus, proprietary traders who can square off positions by the end of the day, are likely to find it easier to short the stock. Thus, it is not surprising that proprietary traders take a more active role in responding to buy recommendations as compared to institutional investors.

Short sale constraints play a role in how these arbitrage strategies are implemented. First, short sales constraints cause individual investors to respond less aggressively to sell recommendations; thus, there is less price pressure due to sell recommendations. Second, institutional investors are more active in responding to sell recommendations than to buy

recommendations because a response to the latter requires shorting of stocks. Proprietary traders are less affected by short sales constraints because they square their trades by the end of the day, and so they are eager to assume contrarian arbitrage positions for both buy and sell recommendations.

5.3. Contrarian profits

To examine whether contrarian positions results in profits, we categorize proprietary traders into deciles based their on net positions in treatment stocks minus those in control stocks at the end of the first half-hour of trading on the day of recommendations. Net position is calculated as value of the shares bought minus value of the shares sold in the recommended stocks. Value, for these opening positions, is calculated by multiplying the number of shares by the opening price of the stock to avoid capturing any effects of price movement in the first half-hour. As argued in Section 5.1 the arbitageurs should establish positions by the first half-hour to maximize profits based on the intra-day price patterns. Indeed, as discussed in Section 5.2, most of the retail investor and contrarian activity seems to be happening in this time frame. We create deciles based on the positions established by the end of first half-hour to examine aggressiveness of arbitrageurs. For buy recommendations, Decile 1 proprietary traders (most negative positions) are the most aggressive arbitrageurs. For sell recommendations, most aggressive arbitrageurs belong to Decile 10. We also compute average gross profit made by proprietary traders in each decile by the end of the day. The end-of-day profit is simply the value of share sold minus value of share bought plus the closing price times the number of outstanding shares long or short at the end of the day.

Table 7 presents, for proprietary traders, the opening positions and end-of-day profits in treatment stocks minus those in control stocks. We begin with buy recommendations (Panel A).

By construction, the difference in first half-hour positions (10 minus 1) is significantly positive, because decile 1 represents proprietary traders who have assumed the largest negative positions. The right half of Panel A shows that end-of day profit differential (10 minus 1) is a statistically significant INR -18,000. This difference indicates that decile 1 proprietary traders enjoy significantly greater end-of-day profits than decile 10 proprietary traders. Consistent with the arbitrage explanation of price behavior, proprietary traders assuming the largest contrarian positions in the first half-hour of trading reap the greatest profits.

Panel B shows the same results for sell recommendations. The end-of-day profit differential (10 minus 1) is not statistically significant. This insignificant profit differential for sell recommendations for proprietary traders could be due to greater competition faced by them from institutional investors. As we have documented in Section 5.2, the institutional investors are active contrarians following sell but not buy recommendations.

Similar to our exercise for proprietary traders, we also examine positions and profits by deciles for institutional investors. Table 8 presents these results. As discussed in Section 5.2, institutional investors are contrarians only following the sell recommendations. Thus focusing on institutional investor activity for sell recommendations in Panel B of Table 8, we again find that more aggressively contrarian traders (Decile 10) make significantly more profit – on an average nearly INR 650 thousand – than less aggressively contrarian traders (Decile 1). Thus, as in the case of proprietary traders following buy recommendation, most aggressively contrarian institutional investors make more money following sell recommendations.

5.4. Limits to arbitrageurs

We consider how arbitrage varies in the cross-section across different stocks. The limits to arbitrage literature suggests that frictions in the trading process will inhibit arbitrageurs. (See

for example, Pontiff (2006) and Vayanos and Gromb (2010)). For instance, arbitrage activity is more costly to implement in illiquid stocks. Thus, one would expect arbitrageurs to assume smaller positions in highly illiquid stocks. We use Illiq, suggested by Amihud (2002), calculated over a period 6 months before to 1 month before the recommendation, as a proxy for frictions in the arbitraging process. Each day we divide the recommended stocks into two groups based on the median Illiq. Table 9 presents results on first half-hour net positions in the treatment stocks (relative to control stocks) and arbitrage profits by proprietary trader decile for each sub-sample. Table 10 does the same for institutional investors.

We find that proprietary trader across deciles assume smaller contrarian positions in more illiquid stocks. For instance, in Panel A (buy recommendations), the net positions of proprietary trader in decile 1 is INR -1.5 million for liquid stocks, but is only INR -0.6 million for illiquid stocks. A similar pattern emerges for sell recommendations (Panel B of Table 8 for proprietary traders and Panel B of Table 9 for institutional investors). For instance, proprietary traders in decile 10, on average, assume contrarian buy positions of INR 1.5 million in liquid stocks but only INR 0.6 million in illiquid stocks. Institutional investors in decile 10, have average net position of about INR 76 million in liquid stocks as opposed to INR 6 million in illiquid stocks.

This finding, which arises for both buy and sell recommendations, for both proprietary traders and institutional investors, resonates strongly with the limits to arbitrage literature, which argues that arbitrageurs will scale back their positions when faced with frictions in the market.

5.5. *Robustness check*

For stocks with derivatives on them, the activity in the spot market in only part of the story. Unfortunately, we do not have data on the trading activity in the derivative markets. So, as a robustness check, we repeat our analysis of intra-day returns and trading for recommended

stocks that do not have derivatives. Stocks without derivatives account for 62% of buy recommendations and 29% of sell recommendations. Figure 9 plots the intra-day returns (treatment minus control) for these recommendations. For both buy and sell recommendations, we see a return pattern similar to Figure 4. First half-our return is about 45 basis points for buy recommendations and about -10 basis points for sell recommendations. Return in Figure 9 for sell recommendations is not statistically significant, most likely to due to small sample size – only 29% of already small sample of sell recommendations correspond to stocks without derivatives.

Figure 10 plots order imbalance of institutional investors and proprietary traders in these stocks. The pattern for trade imbalance is similar. We see that just like in Figures 6 and 7, following buy recommendations, proprietary traders are significant contrarians while institutional investors are not. We do not see any significant pattern following sell recommendations in Figure 10, again possibly due to low power. Overall, the broad pattern of returns and trading holds up for stocks without derivatives.

6. Conclusion

We examine arbitrageur activity following a liquidity shock. We find that, in our setting, TV analysts' pre-market recommendations result in a temporary announcement effect which is completely reversed in less than a week. We argue that given the quick and complete price reversal, any trading in response to the recommendations can be viewed as pure liquidity shock i.e. one that is not accompanied by any change in fundamental value. In the first half-hour of trading, individual investors trade in the direction of the recommendation exerting significant price pressure. Proprietary traders and institutional investors trade in the opposite direction

leaning against the price pressure. Proprietary traders trade contrarian for both buy and sell recommendations. Institutional investors trade contrarian following only sell recommendations. Trading contrarian following buy recommendations involves taking a short position which seems to deter institutional investors. Proprietary traders and institutional investors profit from their contrarian trades confirming that they are indeed arbitraging the temporary price discrepancy due to the recommendations. Proprietary traders and institutional investors assume less aggressive arbitrage positions in the illiquid stocks when compared to the liquid stocks. We thus infer lack of liquidity and short sale constraints as the factors limiting arbitrageur activity and that these limits are applicable differentially across different types of traders.

References

Agarwalla, S.K., Jacob, J. and Varma, J.R., 2013. Four factor model in Indian equities market, Indian Institute of Management, Ahmedabad Working Paper No. 2013-09-05.

Amihud, Yakov, and Haim Mendelson. 1980. Dealership Market. Market-Making with Inventory. *Journal of Financial Economics 8*(1), pp.31–53.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets*, *5*(1), pp.31-56.

Banerjee, A.V. and Duflo, E., 2014. Do firms want to borrow more? Testing credit constraints using a directed lending program. *The Review of Economic Studies*, *81*(2), pp.572-607.

Barber, B.M. and Odean, T., 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors.*Review of Financial Studies*, *21*(2), pp.785-818.

Barber, B.M. and Odean, T., 2013. The behavior of individual investors. Handbook of the Economics of Finance, 2, pp.1533-1570.

Barber, B.M., Lee, Y.T., Liu, Y.J. and Odean, T., 2009. Just how much do individual investors lose by trading?. *Review of Financial studies*, *22*(2), pp.609-632.

Barclay, M.J. and Hendershott, T., 2003. Price discovery and trading after hours. *Review of Financial Studies*, *16*(4), pp.1041-1073.

Beneish, M.D., 1991. Stock prices and the dissemination of analysts' recommendation. *Journal of Business 64*(3), pp.393-416.

Biais, B., Declerck, F. and Moinas, S., 2016. Who supplies liquidity, how and when? *BIS Working Paper No 563*.

Black, F., 1986. Noise. *The journal of finance*, *41*(3), pp.528-543.

Bolster, P.J. and Trahan, E.A., 2009. Investing in Mad Money: price and style effects. *Financial Services Review, 18*(1), pp.69-86.

Busse, J.A. and Green, T.C., 2002. Market efficiency in real time. *Journal of Financial Economics*, *65*(3), pp.415-437.

Carhart, M.M., 1997. On persistence in mutual fund performance. *Journal of finance*, 52(1), pp.57-82.

Chan, W.S., 2003. Stock price reaction to news and no-news: Drift and reversal after headlines. *Journal of Financial Economics*, *70*(2), pp.223-260.

Daniel, K., Grinblatt, M., Titman, S. and Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. *Journal of Finance*, pp.1035-1058.

De Long, J.B., Shleifer, A., Summers, L.H. and Waldmann, R.J., 1990. Noise trader risk in financial markets. *Journal of political Economy*, pp.703-738.

Dougal, C., Engelberg, J., Garcia, D. and Parsons, C.A., 2012. Journalists and the stock market. *Review of Financial Studies*, *25*(3), pp.639-679.

Engelberg, J.E. and Parsons, C.A., 2011. The causal impact of media in financial markets. *The Journal of Finance*, *66*(1), pp.67-97.

Engelberg, J., Sasseville, C. and Williams, J., 2012. Market madness? The case of mad money. *Management Science*, 58(2), pp.351-364.

Evans, A.D., 2009. A Requiem for the Retail Investor?. *Virginia Law Review*, pp.1105-1129.

Fang, L. and Peress, J., 2009. Media coverage and the cross-section of stock returns. *The Journal of Finance*, *64*(5), pp.2023-2052.

Glosten, L.R. and Milgrom, P.R., 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of financial economics*, *14*(1), pp.71-100.

Gopalan, R., Nanda, V. and Seru, A., 2014. Internal capital market and dividend policies: Evidence from business groups. *Review of Financial Studies*, *27*(4), pp.1102-1142.

Gromb, D. and Vayanos, D., 2002. Equilibrium and welfare in markets with financially constrained arbitrageurs. *Journal of financial Economics*, *66*(2), pp.361-407.

Gromb, D., and Vayanos, D., 2010. Limits of Arbitrage. *Annual Review of Financial Economics* 2 (1), pp 251–75.

Grossman, S.J. and Miller, M.H., 1988. Liquidity and market structure. *the Journal of Finance*, *43*(3), pp.617-633.

Gurun, U.G. and Butler, A.W., 2012. Don't believe the hype: Local media slant, local advertising, and firm value. *The Journal of Finance*, *67*(2), pp.561-598.

Hartley, J.S. and Olson, M., 2016. Jim Cramer's 'Mad Money' Charitable Trust Performance and Factor Attribution. University of Pennsylvania Working Paper.

Ho, T. and Stoll, H.R., 1981. Optimal dealer pricing under transactions and return uncertainty. *Journal of Financial economics*, *9*(1), pp.47-73.

Ho, T.S. and Stoll, H.R., 1983. The dynamics of dealer markets under competition. *The Journal of finance*, *38*(4), pp.1053-1074.

Kyle, A.S., 1985. Continuous auctions and insider trading. *Econometrica, 54*(6), pp.1315-1335.

Lilienfeld-Toal, U.V., Mookherjee, D. and Visaria, S., 2012. The distributive impact of reforms in credit enforcement: Evidence from Indian debt recovery tribunals. *Econometrica*, *80*(2), pp.497-558.

Merton, R.C., 1987. A simple model of capital market equilibrium with incomplete information. *The journal of finance*, *42*(3), pp.483-510.

Pontiff, J., 2006. Costly Arbitrage and the Myth of Idiosyncratic Risk. *Journal of Accounting and Economics,* 42 (1-2), pp 35–52.

Shleifer, A. and Vishny, R.W., 1997. The limits of arbitrage. *Journal of Finance*, 52(1), pp.35-55.

Solomon, D.H., 2012. Selective publicity and stock prices. *The Journal of Finance*, *67*(2), pp.599-638.

Solomon, D.H., Soltes, E. and Sosyura, D., 2014. Winners in the spotlight: Media coverage of fund holdings as a driver of flows. *Journal of Financial Economics*, *113*(1), pp.53-72.

Tetlock, P.C., 2007. Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance*, *62*(3), pp.1139-1168.

Tetlock, P.C., Saar-Tsechansky, M. and Macskassy, S., 2008. More than words: Quantifying language to measure firms' fundamentals. *The Journal of Finance*, *63*(3), pp.1437-1467.

Vig, V., 2013. Access to collateral and corporate debt structure: Evidence from a natural experiment. *The Journal of Finance*, *68*(3), pp.881-928.

Visaria, S., 2009. Legal reform and loan repayment: The microeconomic impact of debt recovery tribunals in India. *American Economic Journal: Applied Economics*, pp.59-81.

Weill, P.O., 2007. Leaning against the wind. *The Review of Economic Studies*, *74*(4), pp.1329-1354.

Table 1: Descriptive statistics

This table presents descriptive statistics based on daily values for all BSE-listed stocks from July 1, 2009 to June 30, 2010. In both panels, the values are measured over the indicated period relative to each trading day in the sample period. Ownership Fraction – Individual Investors refers to the percentage of a company's shares held by individual investors. NIFTY/SENSEX Inclusion Indicator is a dummy variable that takes a value of one if a stock is either in the Nifty or the SENSEX and zero otherwise. Benchmark-adjusted returns in Panel B refer to characteristic-adjusted returns as described in Daniel, Grinblatt, Titman, and Wermers (1997).

Panel A: Explanatory Variables

	Return: Day -1	Return: Week -1 to Day -2	Return: Month -1 to Week -1	Return: Month -6 to Month -1	Market Cap	Book to Market Ratio	Average Volume: Day -1	Average Volume: Week -1 to Day -2	Average Volume: Month -6 to Month -1	Ownership Fraction - Individual Investors	NIFTY/ SENSEX Inclusion Indicator	Number of Analysts
					Rs Million		Rs Million	Rs Million	Rs Million			
	%	%	%	%	Million		Million	Million	Million	%		
Mean	0.12	0.37	1.99	26.97	12,835	1.46	41.95	42.13	44.55	32.86	0.01	1.19
Std. Dev.	2.58	4.69	13.02	52.90	100,449	4.00	361.58	340.11	342.28	20.45	0.10	5.34
Percentiles												
5%	-4.61	-6.86	-15.68	-20.05	5	0.13	0.00	0.00	0.00	5.03	0.00	0.00
50%	0.00	0.00	0.00	0.00	156	0.88	0.01	0.02	0.02	29.60	0.00	0.00
95%	4.94	9.67	25.98	128.22	31,955	3.85	91.94	98.51	110.78	72.64	0.00	6.00
Observations	1,216,993	1,216,993	1,216,993	1,216,993	1,118,149	784,531	1,216,993	1,216,993	1,216,993	1,021,408	1,216,993	1,216,993

<u>**Panel B: Outcome Variables**</u>

	Raw Returns						**Benchmark-Adjusted Returns**					
	Day -1 Close to Day 0 Open	**Day 0: Open to Close**	**Day 0**	**Day 0 to 1 week later**	**Day 0 to 1 month later**	**Day 0 to 6 months later**	**Day -1 Close to Day 0 Open**	**Day 0: Open to Close**	**Day 0**	**Day 0 to 1 week later**	**Day 0 to 1 month later**	**Day 0 to 6 months later**
	%	**%**	**%**	**%**	**%**	**%**	**%**	**%**	**%**	**%**	**%**	**%**
Mean	0.23	-0.06	0.12	0.65	3.36	17.93	0.01	-0.01	-0.01	0.02	0.10	0.13
Std. Dev.	2.49	2.93	2.57	6.41	14.88	49.17	2.91	3.47	2.96	7.13	16.60	57.10
Percentiles												
5%	-4.52	-4.95	-4.60	-8.99	-15.52	-26.39	-4.94	-5.61	-4.74	-10.27	-21.60	-62.77
50%	0.00	0.00	0.00	0.00	0.00	0.00	-0.02	-0.08	-0.17	-0.62	-1.78	-8.97
95%	4.89	5.04	4.94	12.90	30.72	100.28	4.86	6.12	5.06	13.35	28.99	87.50
Observations	1,216,993	1,216,993	1,216,993	1,216,993	1,216,993	1,216,993	784,531	784,531	784,531	784,531	784,531	784,531

Table 2: Trader Categories in the Orders and Trade Data

This table shows the original trader categories in the BSE orders and trade data as provided by the exchange and our classification after combining many categories.

Original categories	Our categories
Mutual funds, Foreign institutional investors, Banks, Insurance companies, National pension scheme, Indian financial investor	Institutions
Individuals, Non-resident Indians, Association of persons, Sole proprietor, Hindu undivided family	Individual
Corporations, Partnerships, Trusts, Merchant bankers, Overseas corporate bodies, Qualified foreign investor, Portfolio management scheme, Foreign venture capital fund, Others	Others

Table 3: Conditional Logit for Selection of Batsman and Bowler

This table presents the coefficient estimates and marginal effects of a logit model using daily data from July 1, 2009 to June 30, 2010 for all BSE-listed stocks. Event time is measured relative to each trading day, which is denoted as Day 0. On each trading day, the dependent variable takes a value of one if the stock is included as a Batsman (Bowler) in that day's CNBC Awaaz STOCK 20/20 TV program and zero otherwise. Abnormal Log Volume: Day -1 (Week -1 to Day -2) is the natural logarithm of daily average volume on Day – 1 (over Week -1 to Day -2) minus the natural logarithm of daily average volume over Month -6 to Month -1. Robust z-statistics are presented in parentheses below each coefficient estimate and marginal effect. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Buy Recommendations		Sell Recommendations	
		Marginal		**Marginal**
Explanatory Variables	**Coefficients**	**Effects**	**Coefficients**	**Effects**
Returns				
Return: Day -1	0.210***	0.021***	-0.365***	-0.031**
	(10.149)	(3.213)	(-4.825)	(-2.075)
Return: Week - 1 to Day -2	0.008	0.001	-0.053***	-0.005**
	(1.313)	(1.070)	(-4.403)	(-2.152)
Return: Month -1 to Week -1	0.004**	0.000**	-0.008	-0.001
	(2.001)	(2.049)	(-1.262)	(-1.010)
Return: Month -6 to Month -1	-0.000	-0.000	-0.000	-0.000
	(-0.560)	(-0.607)	(-0.284)	(-0.292)
Volume and Analyst Coverage				
Abnormal Log Volume: Day -1	0.486***	0.048***	0.425***	0.036***
	(12.522)	(5.833)	(3.980)	(6.338)
Abnormal Log Avg Volume: Week -1 to Day -2	0.054	0.005*	0.246***	0.021**
	(1.547)	(1.940)	(3.765)	(2.125)
Log Avg Volume: Month -6 to Month -1	0.788***	0.079***	0.891***	0.076***
	(7.219)	(11.718)	(9.543)	(4.890)
Log (Number of Analysts)	0.825***	0.082***	0.591**	0.050
	(9.658)	(5.569)	(2.463)	(1.604)
(Log Avg Volume: Month -6 to Month -1) x Log (Number of Analysts)	-0.139***	-0.014***	-0.072	-0.006
	(-9.455)	(-3.451)	(-1.278)	(-0.974)

Explanatory Variables	Buy Recommendations		Sell Recommendations	
	Coefficients	**Marginal Effects**	**Coefficients**	**Marginal Effects**
<u>Other Characteristics</u>				
Log(Market Cap): Day -1	-0.113	-0.011	-0.082	-0.007
	(-0.323)	(-0.347)	(-0.133)	(-0.138)
(Book to Market): Day -1	0.096*	0.010	0.136**	0.012
	(1.915)	(1.363)	(2.272)	(1.406)
Ownership Fraction - Individual				
Investors	-0.003	-0.000	-0.014	-0.001
	(-0.135)	(-0.139)	(-0.352)	(-0.390)
NIFTY/SENSEX Inclusion				
Indicator	-0.197	-0.020	-0.093	-0.008
	(-0.498)	(-0.451)	(-0.130)	(-0.125)
Observations	594,870		461,672	
Pseudo R-Squared	0.316		0.393	
Fixed Effects	Day		Day	
S.E. Clustering	Stock		Stock	

Table 4: Distribution of Difference in Propensity Score for Treated and Control Firms

This table presents a distribution of the difference of propensity scores for BSE-listed treatment and control firms. Treatment firms are those that receive a buy or a sell recommendation on the CNBC Awaaz STOCK 20/20 TV program between July 1, 2009 and June 30, 2010. The control stocks are selected by propensity score matching using the conditional logit model in Table 3.

	Buy Recommendations	Sell Recommendations
Mean	0.000214	0.000088
Std. Dev.	0.000406	0.000149
Percentiles		
1%	0.000001	0.000000
5%	0.000007	0.000003
25%	0.000043	0.000016
50%	0.000111	0.000041
75%	0.000242	0.000096
95%	0.000712	0.000330
99%	0.001707	0.000742
Observations	5,036	1,321

Table 5: Event-Day Returns for Propensity-Score Matched Sample

This table presents returns for a sample of BSE-listed companies around the day they are covered on the CNBC Awaaz STOCK 20/20 TV program between July 1, 2009 and June 30, 2010. Day 0 refers to the day on which the stock receives a buy recommendation (Panel A) or a sell recommendation (Panel B). on the TV program. Benchmark-adjusted returns refer to characteristic-adjusted returns as described in Daniel, Grinblatt, Titman, and Wermers (1997). Treatment Minus Control is the difference in returns of treatment firms, which are covered on the TV program on Day 0, and that of propensity-score matched control firms on the same day. The propensity score matching of treatment and control firms is done using the logit model in Table 3. The t-stat, testing the significance of each difference, is in parentheses below. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Panel A: Buy Recommendations

	Raw Returns (%)				Benchmark-Adjusted Returns (%)			
	Day -1	Day -1 Close to Day 0 Open	Day 0: Open to Close	Day 0	Day -1	Day -1 Close to Day 0 Open	Day 0: Open to Close	Day 0
Treatment Minus Control	0.10	1.07***	-0.19***	0.85***	0.07	1.00***	-0.17***	0.81***
	(1.38)	(30.93)	(-2.95)	(13.64)	(1.00)	(30.62)	(-2.80)	(14.07)
Number of Treated	5,036	5,036	5,036	5,036	5,036	5,036	5,036	5,036
Number of Controls	4,663	4,663	4,663	4,663	4,663	4,663	4,663	4,663

Panel B: Sell Recommendations

	Raw Returns (%)				Benchmark-Adjusted Returns (%)			
	Day -1	Day -1 Close to Day 0 Open	Day 0: Open to Close	Day 0	Day -1	Day -1 Close to Day 0 Open	Day 0: Open to Close	Day 0
Treatment Minus Control	-0.01	-0.90***	0.29**	-0.54***	0.01	-0.82***	0.30***	-0.49***
	(-0.10)	(-13.41)	(2.20)	(-4.38)	(0.14)	(-14.95)	(2.63)	(-4.91)
Number of Treated	1,321	1,321	1,321	1,321	1,321	1,321	1,321	1,321
Number of Controls	1,189	1,189	1,189	1,189	1,189	1,189	1,189	1,189

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Table 6: Calendar-Time Portfolio Returns for Propensity-Score Matched Sample

This table presents average daily calendar-time portfolio returns for recommended stocks. On Day 0 the treatment stocks receive a buy recommendation (Panel A) or a sell recommendation (Panel B) on the CNBC Awaaz STOCK 20/20 TV program. DGTW-adjusted returns refer to characteristic-adjusted returns as described in Daniel, Grinblatt, Titman, and Wermers (1997). 4-Factor Alpha is the intercept estimate from the Fama-French-Carhart four-factor model. Treatment Minus Control is the difference in calendar-time portfolio returns of treatment stocks and that of propensity-score matched control stocks. The propensity score matching of treatment and control firms is done using the logit model in Table 3. The sample is from July 1, 2009 to June 30, 2010. The t-stat, testing the significance of each difference, is in parentheses below. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Panel A: Treatment: Buy Recommendations

| | Average Daily Returns Including Previous Close to Open on Day 0 | | | | Average Daily Returns Excluding Previous Close to Open on Day 0 | | | |
| | Treatment | Treatment Minus Control | | | Treatment | Treatment Minus Control | | |
Holding Period	Average Return	Average Return	Average DGTW Adjusted Return	4-Factor Alpha	Average Return	Average Return	Average DGTW Adjusted Return	4-Factor Alpha
1 Day	0.78***	0.88***	0.83***	0.84***	-0.82***	-0.28***	-0.26***	-0.34***
	(6.43)	(12.19)	(11.77)	(11.43)	(-7.84)	(-3.59)	(-3.49)	(-4.31)
5 Days (1 Week)	0.11	0.06*	0.05	0.05	-0.22***	-0.18***	-0.18***	-0.19***
	(1.03)	(1.68)	(1.54)	(1.48)	(-2.13)	(-5.19)	(-5.24)	(-5.43)
22 Days (1 month)	0.11	0.00	0.00	0.00	0.01	-0.07***	-0.07***	-0.08***
	(1.19)	(-0.12)	(-0.03)	(-0.18)	(0.14)	(-3.78)	(-3.72)	(-3.91)
126 Days (6 months)	0.11	0.00	-0.01	0.00	0.08	-0.02*	-0.04***	-0.02
	(1.48)	(-0.19)	(-0.83)	(0.00)	(1.07)	(-1.84)	(-3.12)	(-1.64)
252 Days (1 Year)	0.05	0.01	-0.01	0.01	0.03	0.00	-0.04***	0.00
	(0.86)	(1.23)	(-0.94)	(0.93)	(0.51)	(-0.16)	(-3.23)	(-0.42)

| Holding Period | Including Previous Close to Open on Day 0 | | | | Excluding Previous Close to Open on Day 0 | | | |
| | Treatment | Treatment Minus Control | | | Treatment | Treatment Minus Control | | |
	Average Return	Average Return	Average DGTW Adjusted Return	4-Factor Alpha	Average Return	Average Return	Average DGTW Adjusted Return	4-Factor Alpha
1 Day	-0.82***	-0.79***	-0.72***	-0.75***	0.12	0.22	0.23	0.28
	(-4.24)	(-4.70)	(-4.71)	(-4.36)	(0.69)	(1.27)	(1.40)	(1.59)
5 Days (1 Week)	-0.17	-0.23***	-0.19**	-0.23***	0.02	-0.02	0.01	-0.02
	(-1.24)	(-2.71)	(-2.36)	(-2.70)	(0.18)	(-0.22)	(0.13)	(-0.22)
22 Days (1 month)	0.04	-0.05	-0.07	-0.08*	0.11	0.01	-0.01	-0.02
	(0.38)	(-1.10)	(-1.37)	(-1.68)	(0.94)	(0.14)	(-0.13)	(-0.37)
126 Days (6 months)	0.10	-0.01	-0.01	-0.02	0.11	0.00	0.02	-0.01
	(1.23)	(-0.71)	(-0.27)	(-1.26)	(1.43)	(0.15)	(0.67)	(-0.33)
252 Days (1 Year)	0.04	-0.01	0.00	-0.01	0.05	0.00	0.03	0.00
	(0.57)	(-0.51)	(0.16)	(-0.73)	(0.73)	(0.32)	(1.08)	(0.18)

Note: The "Average Daily Returns" header spans the two groups — "Including Previous Close to Open on Day 0" (left) and "Excluding Previous Close to Open on Day 0" (right).

Table 7: Arbitrage Positions and Profits of Proprietary traders

This table shows net positions of and profits earned by proprietary traders in recommended stocks vs control stocks. We categorize proprietary traders into deciles based their on net positions in the recommended stocks minus those in the control stocks at the end of the first half-hour of trading. Net position = (Shares Bought – Shares Sold) x Opening Price. The profit for day 0 is the value of share sold minus value of share bought plus the closing price times the number of outstanding shares long or short at the end of the day. The sample is from July 1, 2009 to June 30, 2010. The t-stat, testing the significance of each difference, is in parentheses below. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Panel A: Buy Recommendations

Decile	Position at the End of First Half-Hour (Rs '000)		Profit for Day 0 (Rs '000)	
	Mean	Std Dev	Mean	Std Dev
1	-1,138.90	2,300.80	13.93	119.77
2	-250.77	364.47	3.70	35.17
3	-96.29	142.26	2.00	23.88
4	-15.79	47.99	0.22	13.36
5	-0.54	7.52	-0.34	18.88
6	0.07	3.88	0.35	22.43
7	3.28	25.02	0.66	22.35
8	57.55	101.58	-0.72	11.75
9	157.15	269.45	-1.63	18.84
10	707.15	1,388.17	-4.47	64.08
10 minus 1	1,846.05***		-18.40***	
(t-stat)	(75.47)		(-14.98)	

Panel B: Sell Recommendations

Decile	Position at the End of First Half-Hour (Rs '000)		Profit for Day 0 (Rs '000)	
	Mean	Std Dev	Mean	Std Dev
1	-918.74	1,574.20	1.36	79.28
2	-187.46	241.50	1.13	24.61
3	-60.82	106.86	2.02	23.58
4	-2.56	23.36	0.34	12.42
5	0.25	13.19	-0.07	27.50
6	1.19	37.14	0.50	21.43
7	20.29	189.54	2.88	31.41
8	115.02	441.05	1.48	19.41
9	241.49	876.30	0.29	47.63
10	1,074.93	3,009.46	0.27	174.15
10 minus 1	1,993.67***		-1.09	
(t-stat)	(36.94)		(0.36)	

Table 8: Arbitrage Positions and Profits of Institutional Investors

This table shows net positions of and profits earned by institutional investors in recommended stocks vs control stocks. We categorize institutional investors into deciles based their on net positions in the recommended stocks minus those in the control stocks at the end of the first half-hour of trading.. Net position = (Shares Bought – Shares Sold) x Opening Price. The profit for day 0 is the value of share sold minus value of share bought plus the closing price times the number of outstanding shares long or short at the end of the day. The sample is from July 1, 2009 to June 30, 2010. The t-stat, testing the significance of each difference, is in parentheses below. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Panel A: Buy Recommendations

Decile	Position at the End of First Half-Hour (Rs '000)		Profit at the end of the day (Rs '000)	
	Mean	Std Dev	Mean	Std Dev
1	-13,927.30	60,539.63	8.62	1,510.19
2	-4,567.18	17,608.45	84.69	625.17
3	-1,965.27	6,202.86	76.71	888.84
4	-241.98	970.18	-6.61	531.69
5	-5.62	92.12	1.93	447.74
6	-0.13	18.57	0.66	1,255.28
7	111.56	955.11	-12.61	498.12
8	1,050.32	2,712.26	-19.23	327.49
9	4,960.15	25,383.11	-30.46	568.60
10	13,184.86	47,458.18	-49.24	1,790.56
10 minus 1	27,112.16***		-57.86	
(t-stat)	(8.83)		(-0.62)	

Panel B: Sell Recommendations

Decile	Position at the End of First Half-Hour (Rs '000)		Profit for Day 0 (Rs '000)	
	Mean	Std Dev	Mean	Std Dev
1	-13,984.89	29,859.25	141.87	1,469.48
2	-4,558.85	12,611.66	62.62	683.17
3	-836.68	2,060.59	26.03	331.93
4	-65.92	456.79	-10.77	220.22
5	1.29	147.59	-4.40	335.86
6	11.49	459.63	0.60	317.18
7	1,012.97	7,759.77	33.43	343.56
8	4,852.77	15,556.53	103.87	536.05
9	6,372.59	22,574.01	40.85	459.49
10	37,563.64	186,161.49	788.55	5,778.81
10 minus 1	51,548.53***		646.68**	
(t-stat)	(5.51)		(2.18)	

Table 9: Arbitrage Positions of Proprietary traders: Liquid and Illiquid Stocks

This table shows net positions of earned by proprietary traders in liquid and illiquid recommended stocks vs control stocks. We classify recommended stocks into liquid and illiquid each day based on median of Amihud (2002) Illiq measure, calculated over a period from 6 months ago to 1 month ago. For each type of stocks, we categorize proprietary traders into deciles based their on net positions at the end of the first half-hour of trading in treatment stocks minus those in control stocks. Net position = (Shares Bought – Shares Sold) x Opening Price. The sample is from July 1, 2009 to June 30, 2010. The t-stat, testing the significance of each difference, is in parentheses below. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Panel A: Buy Recommendations

Decile	Position at the End of First Half-Hour (Rs '000)			
	Liquid Stocks		Illiquid Stocks	
	Mean	Std Dev	Mean	Std Dev
1	-1,544.22	2,759.92	-619.69	1,279.61
2	-344.51	427.60	-143.71	225.35
3	-130.61	170.49	-56.68	83.47
4	-33.04	70.75	-10.48	32.80
5	-0.95	10.74	-0.69	7.97
6	0.06	3.92	0.07	4.29
7	2.25	20.11	4.08	31.14
8	54.37	97.93	40.84	74.34
9	155.37	223.54	118.11	293.81
10	779.21	1,754.40	499.16	917.42
10 minus 1	2,323.44***		1,118.85***	
(t-stat)	(55.03)		(39.73)	

Panel B: Sell Recommendations

Decile	Position at the End of First Half-Hour (Rs '000)			
	Liquid Stocks		Illiquid Stocks	
	Mean	Std Dev	Mean	Std Dev
1	-1,275.72	1,908.52	-538.07	936.41
2	-249.05	276.19	-134.07	177.79
3	-82.13	126.85	-40.62	64.37
4	-4.73	36.57	-3.00	19.56
5	0.81	20.84	-0.15	5.31
6	2.74	58.20	0.10	3.27
7	43.69	304.17	5.26	32.11
8	196.75	689.35	42.59	98.47
9	334.17	1,301.03	133.53	241.54
10	1,466.24	4,278.65	568.39	1,455.53
10 minus 1	2,741.96***		1,106.46***	
(t-stat)	(24.43)		(20.00)	

Table 10: Arbitrage Positions of Institutional Investors: Liquid and Illiquid Stocks

This table shows net positions of earned by institutional investors in liquid and illiquid recommended stocks vs control stocks. We classify recommended stocks into liquid and illiquid each day based on median of Amihud (2002) Illiq measure, calculated over a period from 6 months ago to 1 month ago. For each type of stocks, we categorize institutional investors into deciles based their on net positions at the end of the first half-hour of trading in treatment stocks minus those in control stocks. Net position = (Shares Bought – Shares Sold) x Opening Price. The sample is from July 1, 2009 to June 30, 2010. The t-stat, testing the significance of each difference, is in parentheses below. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Panel A: Buy Recommendations

| Decile | Position at the End of First Half-Hour (Rs '000) | | | |
| | Liquid Stocks | | Liquid Stocks | |
	Mean	Std Dev	Mean	Std Dev
1	-15,785.42	75,657.13	-4,516.00	7,707.37
2	-5,569.50	21,493.61	-2,017.81	2,956.34
3	-2,072.64	7,689.61	-2,079.62	6,462.57
4	-321.33	1,211.24	-418.53	1,264.42
5	-3.43	67.13	-15.69	141.43
6	-0.33	16.05	0.15	21.69
7	128.58	1,430.34	154.34	803.39
8	1,188.07	2,953.74	756.92	1,396.79
9	7,266.60	36,818.87	1,974.80	6,727.55
10	15,843.52	54,306.25	4,728.90	6,816.57
10 minus 1	31,628.94***		9,244.90***	
(t-stat)	(6.05)		(5.56)	

Panel B: Sell Recommendations

| Decile | Position at the End of First Half-Hour (Rs '000) | | | |
| | Liquid Stocks | | Liquid Stocks | |
	Mean	Std Dev	Mean	Std Dev
1	-16,631.93	35,077.01	-7,504.99	19,316.60
2	-4,431.59	5,913.27	-2,692.71	3,920.63
3	-652.29	1,734.99	-1,390.00	2,901.80
4	-174.67	874.92	-25.80	148.35
5	8.33	195.35	-11.68	209.00
6	32.70	741.57	0.40	11.64
7	2,961.45	13,325.47	89.22	390.54
8	12,404.24	26,255.09	2,193.94	6,574.27
9	10,828.28	32,403.02	2,255.65	4,424.04
10	76,219.78	285,775.02	6,439.28	12,089.76
10 minus 1	92,851.71***		13,944.27***	
(t-stat)	(4.17)		(4.31)	

Figure 1: Cumulative Abnormal Returns around Recommendations.

This figure plots cumulative abnormal returns (CAR) for treatment firms minus those of control firms for an event window around stock recommendations. On Day 0 the treatment stocks receive buy recommendations (Panel A) or sell recommendations (Panel B) on the CNBC Awaaz STOCK 20/20 TV program. The control stocks are selected by propensity score matching using the conditional logit model in Table 3. Abnormal returns i.e. DGTW-adjusted returns refer to characteristic-adjusted returns as described in Daniel, Grinblatt, Titman, and Wermers (1997). Solid line shows the mean return and dashed lines show the 95% confidence bounds.
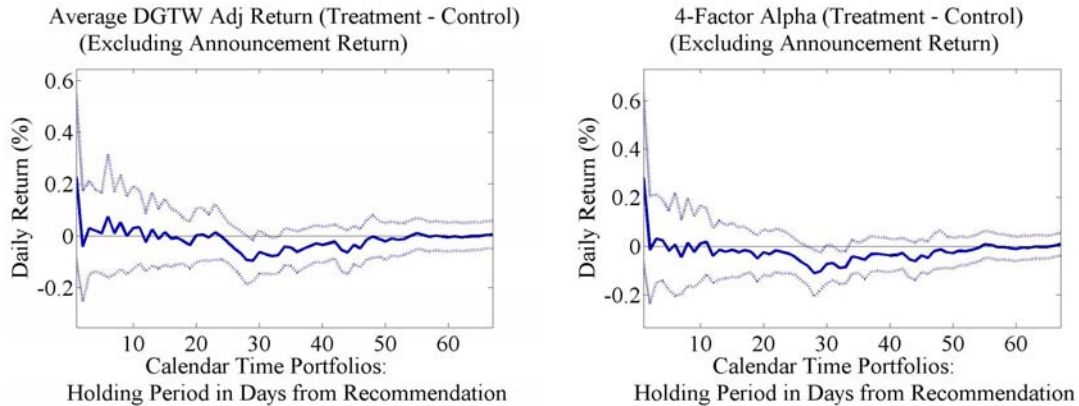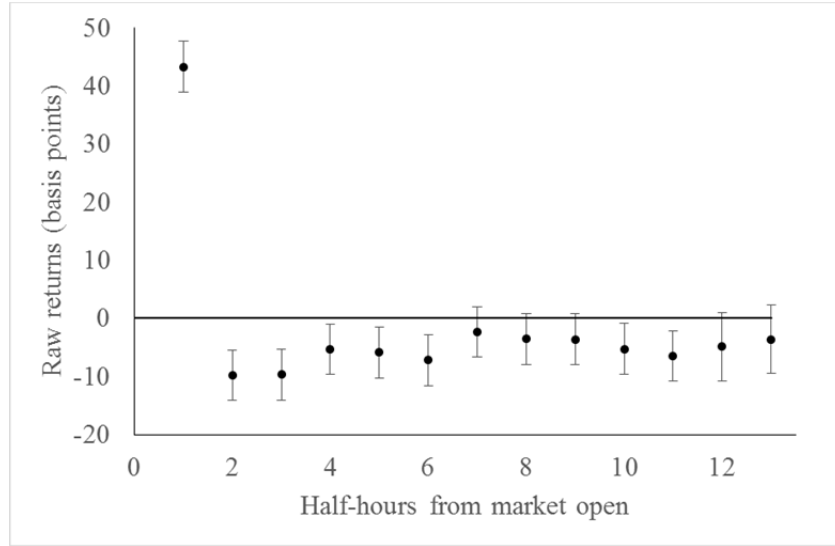
Panel A: Buy Recommendations

Cumulative Abnormal Returns (Treatment - Control)

Panel B: Sell Recommendations

Cumulative Abnormal Returns (Treatment - Control)
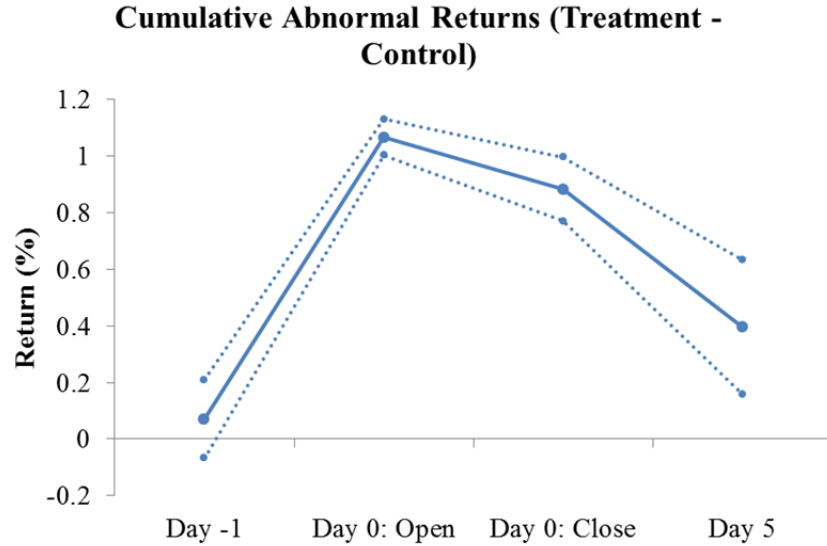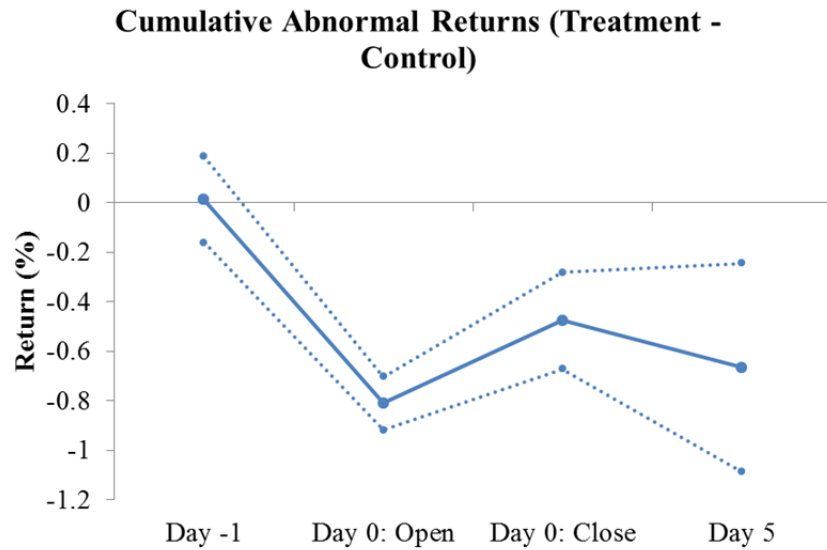
Figure 2: Return: Calendar-Time Portfolios.

This figure plots daily calendar-time portfolio returns of treatment firms minus that of control firms for a three-month period (66 trading days) after the treatment stocks receive buy recommendations (Panel A) or sell recommendations (Panel B) on the CNBC Awaaz STOCK 20/20 TV program. The control stocks are selected by propensity score matching using the conditional logit model in Table 3. DGTW-adjusted returns refer to characteristic-adjusted returns as described in Daniel, Grinblatt, Titman, and Wermers (1997). 4-Factor Alpha is the intercept estimate from the Fama-French-Carhart four-factor model. The returns *include* announcement effect i.e. return from the previous day's closing price to the opening price on the day of recommendation. Solid line shows the mean return and dashed lines show the 95% confidence bounds.

<u>**Panel A: Buy Recommendations**</u>

<u>**Panel B: Sell Recommendations**</u>

Figure 3: Reversal: Calendar-Time Portfolios.

This figure plots daily calendar-time portfolio returns of treatment firms minus that of control firms for a three-month period (66 trading days) after the treatment stocks receive buy recommendations (Panel A) or sell recommendations (Panel B) on the CNBC Awaaz STOCK 20/20 TV program. The control stocks are selected by propensity score matching using the conditional logit model in Table 3. DGTW-adjusted returns refer to characteristic-adjusted returns as described in Daniel, Grinblatt, Titman, and Wermers (1997). 4-Factor Alpha is the intercept estimate from the Fama-French-Carhart four-factor model. The returns *include* announcement effect i.e. return from the previous day's closing price to the opening price on the day of recommendation. Solid line shows the mean return and dashed lines show the 95% confidence bounds.

Panel A: Buy Recommendations

Panel B: Sell Recommendations

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Figure 4: Intra-day Returns.

This figure plots the difference in half-hour returns (in bps) between treatment and control stocks, along with a 95% confidence interval on the day the treatment stocks receive buy recommendations (Panel A) or sell recommendations (Panel B) on the CNBC Awaaz STOCK 20/20 TV program between July 1, 2009 and June 30, 2010. The control stocks are selected by propensity score matching using the conditional logit model in Table 3.

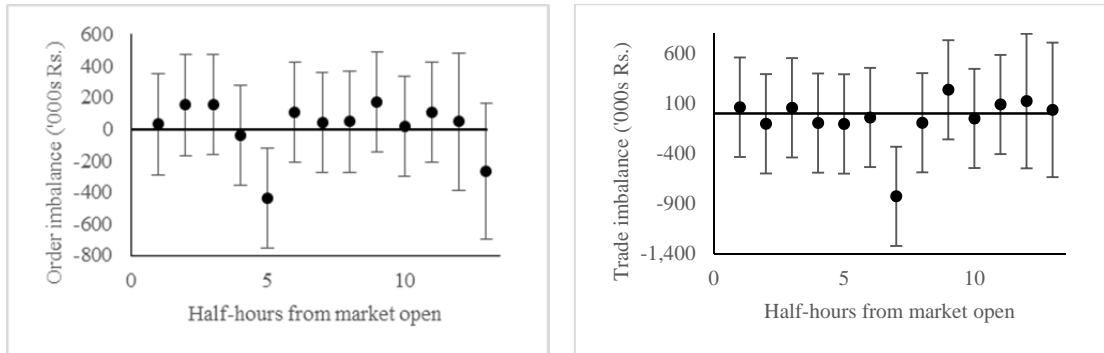**Panel A: Buy Recommendations**

Panel B: Sell Recommendations
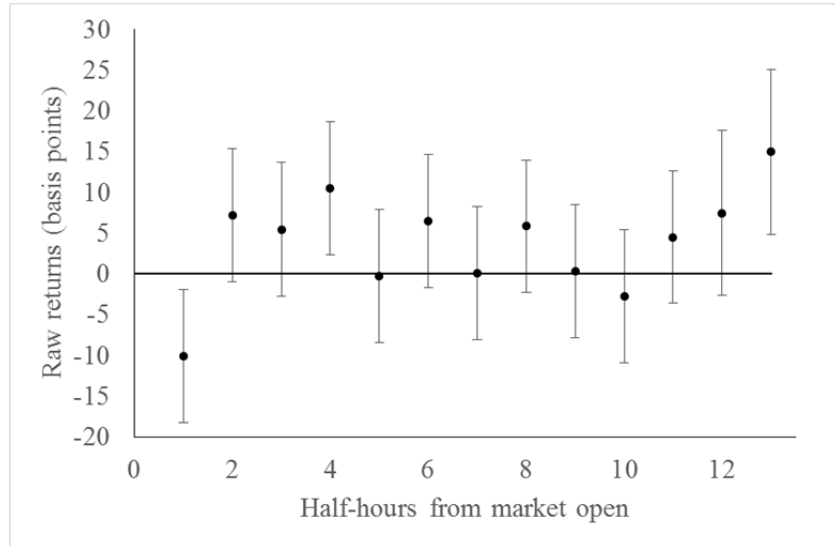
Figure 5: Trading by Individual Investors on Recommendation Day.

This figure plots the difference in order and trade imbalance of individual investors (in thousands of rupees) between treatment and control stocks, along with a 95% confidence interval on the day the treatment stocks receive buy recommendations (Panel A) or sell recommendations (Panel B) on the CNBC Awaaz STOCK 20/20 TV program between July 1, 2009 and June 30, 2010. The control stocks are selected by propensity score matching using the conditional logit model in Table 3. The plots on the left are based on order imbalance calculated using trade-triggering orders submitted by individual investors and the ones on the right are based on trade imbalance calculated using all executed orders submitted by individual investors.

Panel A: Buy Recommendations
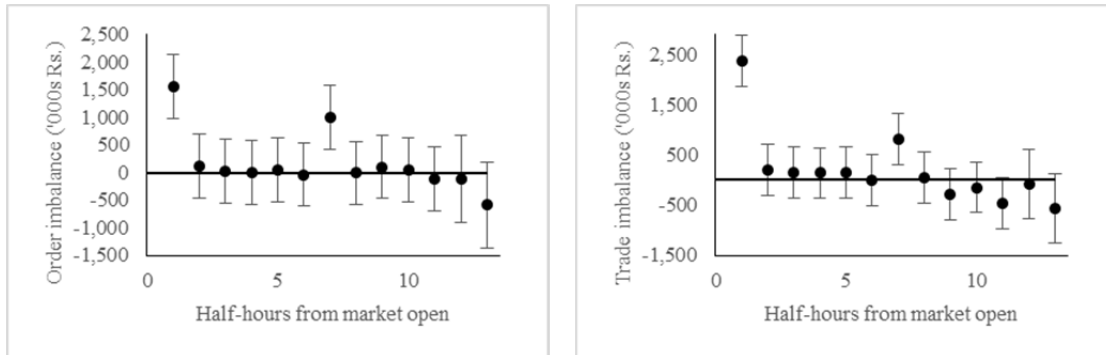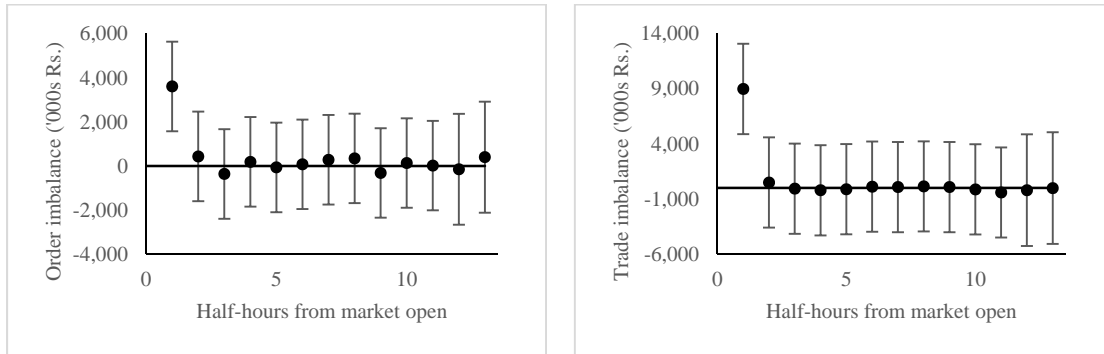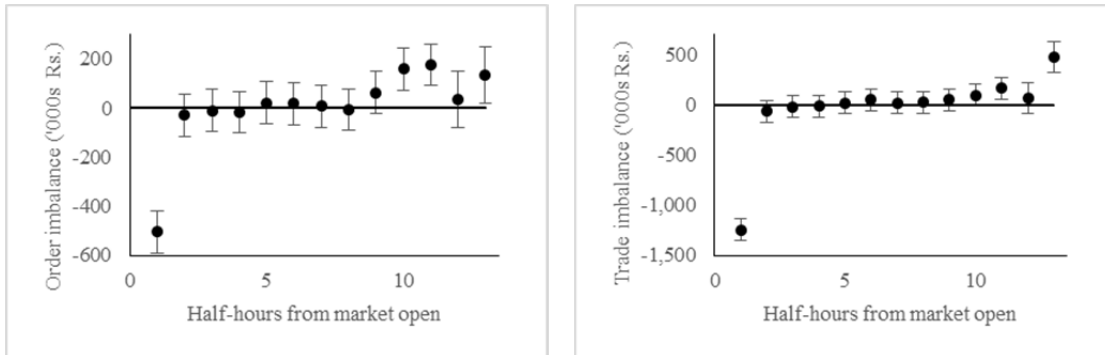

Panel B: Sell Recommendations
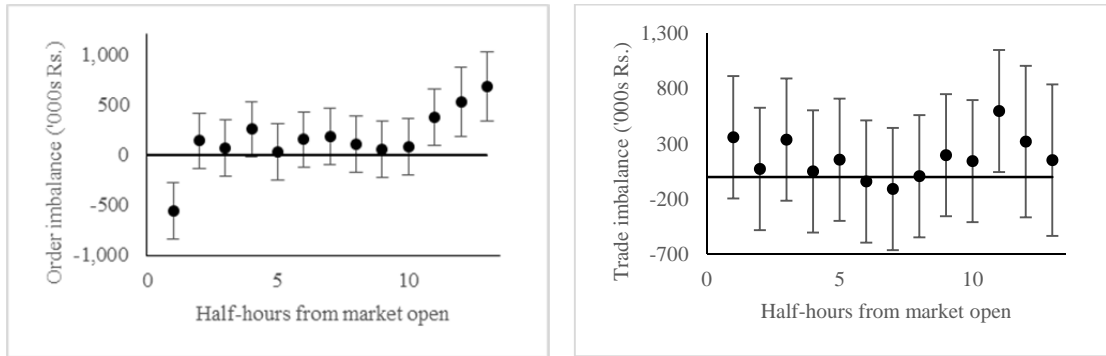
Figure 6: Trading by Institutional Investors on Recommendation Day.

This figure plots the difference in order and trade imbalance of institutional investors (in thousands of rupees) between treatment and control stocks, along with a 95% confidence interval on the day the treatment stocks receive buy recommendations (Panel A) or sell recommendations (Panel B) on the CNBC Awaaz STOCK 20/20 TV program between July 1, 2009 and June 30, 2010. The control stocks are selected by propensity score matching using the conditional logit model in Table 3. The plots on the left are based on order imbalance calculated using trade-triggering orders submitted by institutional traders and the ones on the right are based on trade imbalance calculated using all executed orders submitted by institutional traders.

<u>**Panel A: Buy Recommendations**</u>

<u>**Panel B: Sell Recommendations**</u>

Figure 7: Trading by Proprietary Traders on Recommendation Day.

This figure plots the difference in order and trade imbalance of proprietary traders (in thousands of rupees) between treatment and control stocks, along with a 95% confidence interval on the day the treatment stocks receive buy recommendations (Panel A) or sell recommendations (Panel B)on the CNBC Awaaz STOCK 20/20 TV program between July 1, 2009 and June 30, 2010. The control stocks are selected by propensity score matching using the conditional logit model in Table 3. The plots on the left are based on order imbalance calculated using trade-triggering orders submitted by proprietary traders and the ones on the right are based on trade imbalance calculated using all executed orders submitted by proprietary traders.

Panel A: Buy Recommendations

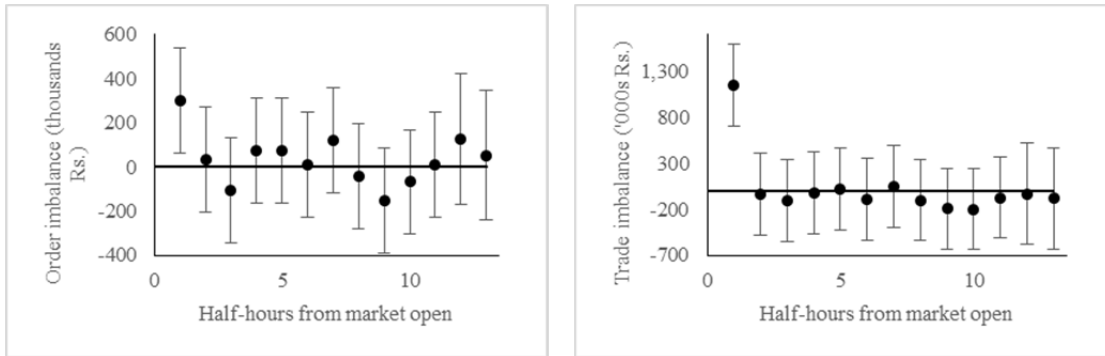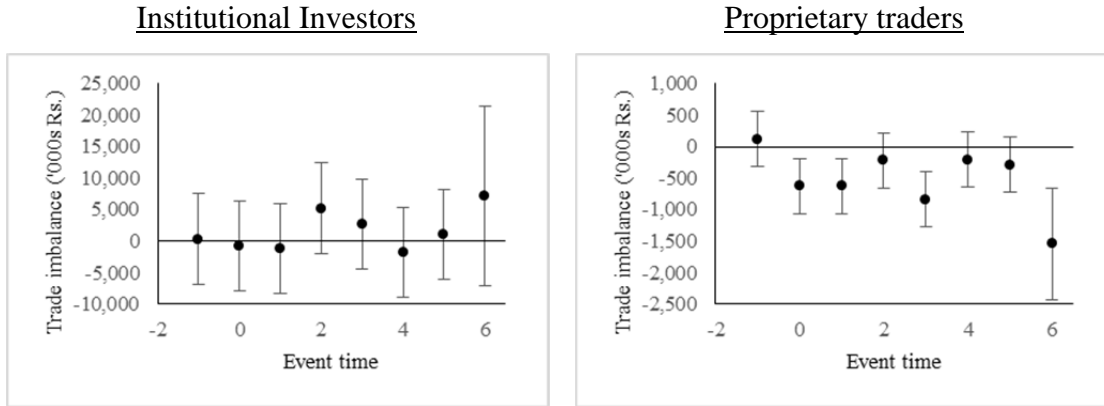

Panel B: Sell Recommendations

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Figure 8: Daily Trading by Institutional Investors and Proprietary Traders.

This figure plots the difference in trade imbalance of institutional investors and proprietary traders (in thousands of rupees) between treatment and control stocks, along with a 95% confidence interval, for different days around day of recommendation. Day 0 is the day the treatment stocks receive buy recommendations (Panel A) or sell recommendations (Panel B) on the CNBC Awaaz STOCK 20/20 TV program. Sample is from July 1, 2009 to June 30, 2010. The control stocks are selected by propensity score matching using the conditional logit model in Table 3. The plots are based on trade imbalance calculated using all executed orders submitted by each category.

Panel A: Buy Recommendations

Institutional Investors   Proprietary traders

Panel B: Sell Recommendations

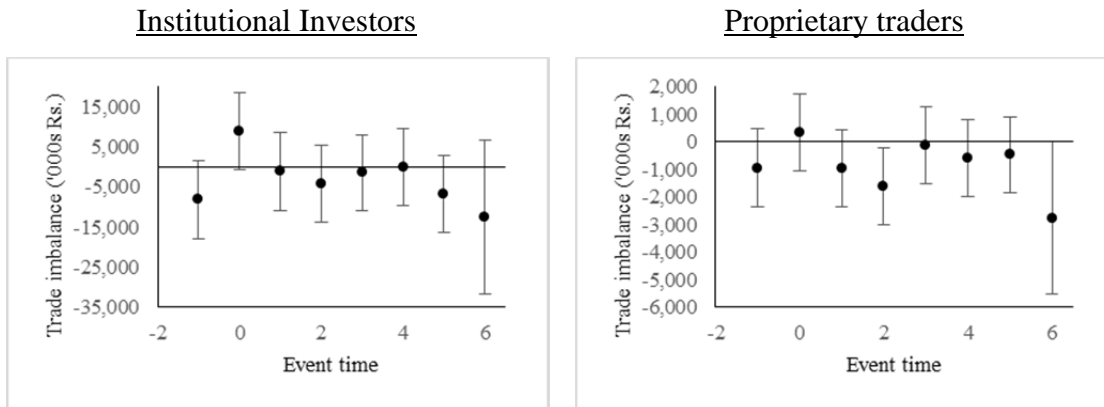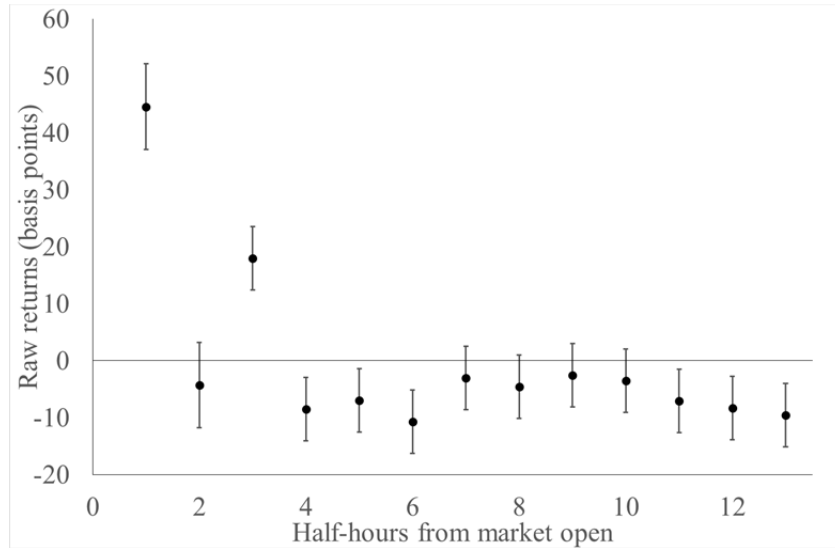Institutional Investors   Proprietary traders

Figure 9: Intra-day Returns: Stocks without Derivatives.

This figure plots the difference in half-hour returns (in bps) between treatment stocks without derivatives on them and their corresponding control stocks, along with a 95% confidence interval on the day the treatment stocks receive buy recommendations (Panel A) or sell recommendations (Panel B) on the CNBC Awaaz STOCK 20/20 TV program between July 1, 2009 and June 30, 2010. The control stocks are selected by propensity score matching using the conditional logit model in Table 3.

Panel A: Buy Recommendations

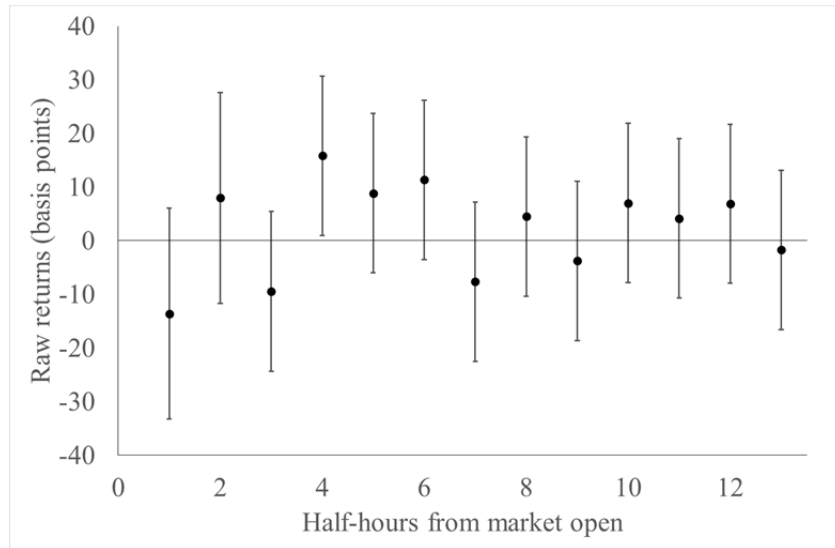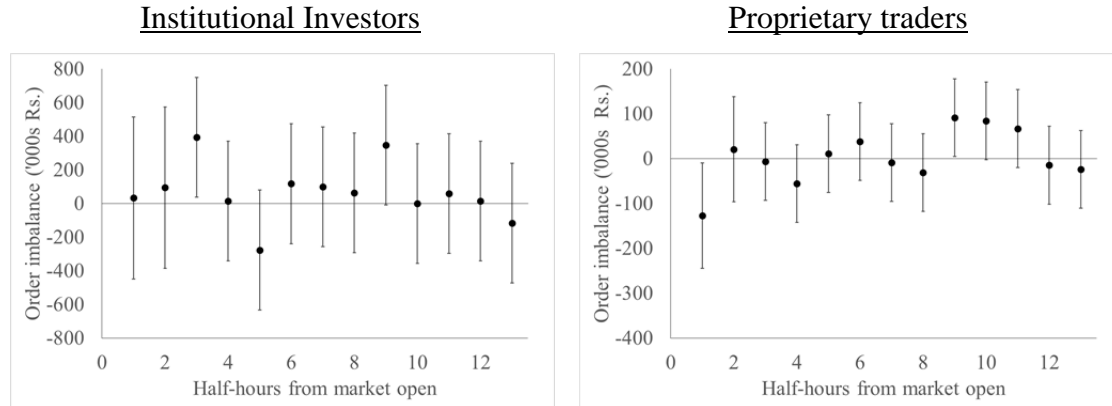**Panel B: Sell Recommendations**

Figure 10: Trading on Recommendation Day in Stocks without Derivatives

This figure plots the difference in order imbalance of institutional investors and proprietary traders (in thousands of rupees) between treatment stocks without derivatives on them and their corresponding control stocks, along with a 95% confidence interval on the day the treatment stocks receive buy recommendations (Panel A) or sell recommendations (Panel B) on the CNBC Awaaz STOCK 20/20 TV program between July 1, 2009 and June 30, 2010. The control stocks are selected by propensity score matching using the conditional logit model in Table 3. Order imbalance is calculated using liquidity-demanding orders.

Panel A: Buy Recommendations

Institutional Investors

Proprietary traders

Panel B: Sell Recommendations

Institutional Investors

Proprietary traders