Behavioral Collective Action: Thousand Effect in China Stock Market

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I. INTRODUCTION

How do people cope with coordination problems in collective actions when they are faced with too many possibilities of pure-strategy equilibria. Schelling(1960 [1]) argued that coordination is sometimes achieved when all involved parties anticipate and intend to realize the salient equilibria, that is, some focal points for each persons expectation of what the other expect him to be expected to do. In practice, the notion of focal point is associated with high success rate of coordination as Mehta, Starmer and Sugden(1994 [2] [3]) and Bacharach and Bernasconi(1997 [4]) observe. Nevertheless, the robustness of focal point theory has been challenged by scholars like Crawford, Gneezy and Rottenstreich(2008 [5]). Other than the spontaneous choosing of salient strategies, successful coordination within a group of players is sometimes attained through intentionally-designed mechanism that aims to solve the dilemmas of collective action. Since Olsen(1965 [6]), a number of scholars have proposed to bridge the gap between the theoretical discussions of coordinating collective action and their real-life implications, e.g. McCabe, Rassenti and Smith(1996 [7]) and Fehr and Schmidt(1999 [8]). Among them, Ostrom(1998 [9], 2000 [10]) provides a framework that emphasized the role of behavioral elements like reciprocity, reputation and trust in resolving coordination problems of collective action. However, the framework has not been rigorously theorized or empirically tested. We argue in this paper that behavioral elements can play a significant role in coordinating collective actions. To substantiate such claim, we formulate a theoretical model and present empirical evidence.

We place our research in the setting of Chinese stock market. We find that the instructing role of market fundamentals on stock exchange is weakened when investors are engaged in the collective action known as chasing the market, i.e. the entering or exiting stock market with the intention of profiting from an occurring trend of price movement. Indeed, it is frequently observed in Chinese stock market that stock prices keep rising unboundedly when fundamentals are not looking that promising, and a slump always ensues. The setting can be simplified to a game of collective action, in which the price slump is the realized equilibrium when investors collectively choose to exit the market. Theoretically, a slump is probable at any time during the market-chasing game for investors will eventually withdraw out of impatience. However in practice, we notice the fact that slumps occur with substantially higher frequency when market index are close to numbers with salient feature. Such phenomenon we will be referred to as round-number effect throughout this proposal.

It suggests that some investors wont sell their stockholding until the price approaches those round numbers. And once those traders with somewhat absurd inclination to round numbers withdraw their investment, other investors react to withdraw as well, and such frequent exits breaks the bubble. Note that rational investors do not have to wait until their irrational counterparts actually leave the market. Indeed, having anticipated the irrational behaviors, rationality entails that they exit when stock market get close enough to round numbers regardless of the exact timing of exit for irrational investors. In such way, the round-number effect is translated into a coordination game, where a behavioral element of some investors inclining to round-numbers is chosen by rational players as a focal point for collectively quitting the market-chasing game, narrowing the set of possible equilibria to an interval around round-numbers.

Previous studies have suggested that what the exact number of stock prices or stock indices look like affects stock market fluctuations. Some investors are found to favor numbers with certain ending digits (e.g. number 8 is preferred in China, as found by Brown, Chua and Mitchell in 2002 [11], and Rao, Zhao and Yue in 2008 [12]), leading to the phenomenon of price clustering. Clustering of stock prices around 0-ended or 5-ended numbers is common, which is consistent with observations from other asset markets. It is argued that investors prefer those numbers for convenience and in an attempt to reduce transaction costs (see Osborne 1962 [11], Niederhoffer 1965 [12], 1966 [13], Harris 1991 [14] and Grossman et al. 1997 [15]). In contrast, as for stock indices, the reverse clustering effect prevails.

Studies find that the frequency of Dow Jones Industrial Average (DJIA) (Donaldson and Kim 1993 [16]) and Shanghai Composite Index (SCI) (Zhao and Yue 2006 [17]) being at 50s and 100s multiple is significantly lower than other numbers. Donaldson and Kim(1993 [16]) and Ley and Varian(1994 [18]) propose the theory of psychological barriers to explain such clustering of stock indices. Evidence suggests that the probability and magnitude of subsequent rises (falls) are larger when stock indices go up (down) through the barriers, and the total trade volume is higher when indices approach round numbers. The prospect that market index will break through the barriers appears to have stimulated positive market sentiments. Yue and Zhao(2007 [19]) suggest psychological barrier also applies to stock prices. Quite contrary to the fact that retail prices ending with 9 or 99 will stimulate demand and increase profits because of consumers inattention to right digits (Anderson and Simester 2003a [20], b [21]), with the existence of psychological barrier, investors tend to degrade the value of stocks with 9-ended prices. Indeed, Bagnoli(2006 [22]) points out that on New York Stock Exchange (NYSE) or Nasdaq, 9-ending prices is commonly associated with increase in trade volume propelled by increased attempts to sell.

The rest of the proposal is organized as follows. Section 2 reviews relevant literature on focal point theory and advances our theoretical model. Section 3 introduces our data and empirical design, some results are presented as well. Section 4 concludes and provide a future plan of research.

II. Theoretical Framework

Literature and Insight. The literature of focal point theory[1] seems limited either in patterns of behavioral cooperation among a comparatively small group, e.g. Bacharach(1993 [24]), Sudgen(1995 [25]) and Janssen(2000 [26]); in experimental circumstances, e.g. Cooper, DeJong, Forsythe and Ross(1990 [27]) and Mehta, Starmer and Sudgen(1994ab [2], [3]); or in design of mechanisms and search of equilibria through non-behavioral manner, e.g. Crawford and Haller(1990 [28]) and McAdams and Nadler(2005 [29]). Furthermore, scholars like Crawford, Gneezy and Rottenstreich(2008 [5]) point out the unrobustness of focal point in some games which are similar to those discussed in previous literature, however, with asymmetric perturbation.

One of the most severe problems emerging in discussions on focal point theory lies in the neglect of behavioral collective action, the framework of the role that irrational behavior patterns play in coordination among many people or even societies. Actually, the enlightening theory raised by Ostrom(1998 [9]) emphasizes the importance of social norms that contain behavioral inclinations such as reciprocity, reputation and trust. This study subsequently incurred very heated investigation on the origin(e.g. Uslaner in 2002 [30], and Lee and See in 2004 [31]) and function(e.g. Fehr and Gachter in 2000 [32]) of human behavioral patterns that serve as salutary tools in economic coordination.

According to and inspired by Ostrom's theory, we provide a structural framework[2] here: behavioral characteristics are some exogenous *heuristics* helping to select one or a few of the most salient equilibria among the comparatively large equilibrium set, and thus coordination is secured; and furthermore, now that the realized coordination is itself an equilibrium, which means in this outcome everyone reaches rationality, collective action remains stable with coordination repeated, equilibrium learned and the original heuristics reinforced, and eventually behavioral inclinations become social norms. Nevertheless, the framework above has not been very well formulated before.

[1]For more complete review, see Janssen [23] or Ostrom [9]

[2]In the original paper, the framework has not been interpreted in equilibrium contexts, however, to include social behavior within game structure seems important to institutional analysis.

Background and Assumptions. We will present our contribution below by utilizing a game model depicting the market-chasing process in asset markets in order to clarify the logic of behavioral collective action. Market-chasing, as discussed earlier, refers to the phenomenon on stock market that when the price has been climbing quickly, which usually cannot or can only partly be explained by fundamental background, it tends to increase as if ceaselessly, although the chasing will eventually cease and engender sharp slump. The problem is that without the guidance of fundamentals, how will the behavior of traders be determined, or specifically, when will the slump occur?

We propose that behavioral heuristics serves as a significant determinant. The heuristics in our model is the *Round-Number Effect* mentioned in the previous section. According to this effect, we assume that there exists a belief held strictly by proportional population of traders that the price will slump at a specific level, say P^*, and therefore these irrational traders will sell their assets either when price stands on P^*, or when the slump occurs beforehand.

Instead of directly modelling stock market, we choose to consider a simplified game of multi-stage investment. This simplification needs to be justified: if we intend to illustrate a stock market, the heterogeneity among players has to be in consideration, since it is the realized transactions that determine the price, and any transaction implies different expectation of traders; however, the market-chasing process that we are concerned seems to be a symmetric collective action for most of the part, so to include heterogeneity will only make the analysis unnecessarily involved.

To convey our insight without complicating the setting, several assumptions and justifications are needed to qualify the multi-stage investment game. Firstly, we postulate that fundamentals(e.g. the quality of assets) provide no information, and this prerequisite is understandable for this is how we present a market-chasing. Secondly, we assume that the traders are not sufficiently patient, and consequently the slump will eventually appear. Thirdly, the market consists of numerous un-pivotal traders such that no one is able to significantly affect price; this assumption is reasonable since the price in model is actually stock indices usually relating to operation of tremendous volume of capital. Fourthly, we posit that the price is positively related to aggregate investment; and the intrinsic logic of this assumption lies in the fact that stock price is determined by realized transactions where some traders have to tolerate costs to enter the market, thus aggregate investment composed of the costs that traders currently tolerate determines the price; and in our simplified investment game, we change *positively related* to *equal* to further reduce complication. Lastly, we assume that when one exits the market, it sells all its assets and gains a fortune positively related to what it has lastly owned, which is calculated by multiplying the amount of owned assets by the price of the last stage; however, this posit seems confusing, because many people get trapped and fail to evacuate so that they gain nothing; but we point out that it is reasonable to assume a positive ex ante probability of successful escaping, because otherwise market-chasing phenomenon will not even happen given nothing to gain.

The Base Model. There are N investors in a public investment project[3] where N is bounded but large enough. The project is an infinite-stage game providing every investor opportunity to invest on a public good which cannot directly yield utility to the buyers, nonethless, since the price equals the aggregate investment and when an investor exits the project it faces a positive probability of taking away its share of the good, participants will not necessarily exit at once and market-chasing is possible.

Specifically, $i = 1, 2, ..., N$ represents the ith investor and $k \in \mathbb{N}$ the kth stage, and P_k is the price of the public good at stage k whereas $q_k^{(i)}$ denotes the share of investment that i owns at stage k, or equivalently, $q_k^{(i)}$ equals the cost that i has paid so far. The price is given by $P_k = \sum_{i=1}^{N} q_{k-1}^{(i)}$, which corresponds to the fourth assumption mentioned in the last subsection. Every investor owns e_0 share of the investment at stage zero[4], and as long as the investor is still in market, it has two and only two available options at each stage: either to chase the price by making investment and owning another e_1 share; or to exit the market, claim the investment it lastly owns with a success probability $\eta > 0$ and consequently gain overall $u_k^{(i)}$[5] $= \eta\beta^k(P_{k-1}q_{k-1}^{(i)} - q_{k-1}^{(i)})$ where $\beta < 1$ is the discount factor. Once an investor exits, no action of its is available hereafter. Obviously, $q_k^{(i)}$ is subjected to

$$q_k^{(i)} = \begin{cases} e_0 + ke_1, & if\ i\ is\ in\ market \\ 0, & otherwise. \end{cases}$$

In this way, a simplified, intuitive but insightful model depicting fundamental-free asset markets is constructed, and the five assumptions from the last subsection are all incorporated.

[3]These investors are almost equivalent to traders in stock market, and the only difference is that, in the simplified investment game, investors only need to decide whether to invest but do not need to wait for an opponent trader. Likewise, the project here is a proxy of stock market. The motivation of this setting has been clarified in preceding paragraphs.

[4]This setting is irrelevant to the ultimate general solution, but to imitate stock market, we let everyone owns something initially.

[5]This is only an approximate expression, but since N is a sufficiently large number, it will not affect the form of eventual solution. Readers may check it by themselves.

The Behavioral Model. In base model, we make an underlying assumption that every player in the game is rational and pursues optimization given others' choices. To introduce the behavioral heuristics, round-number effect, into analysis, we need to make some alternations. Besides the five postulates, we further assume that there exist $M < N$ irrational investors who hold strictly the belief that the price will fall sharply when it reaches a specific level P^*. So the behavior pattern of irrational investors is definite, namely they always choose to chase the price unless two events happen at the last stage: when the price stands on P^*, or when the number of exits so far is greater than m which satisfies $\frac{1}{2}N < m < N$. We denote $\theta = \frac{M}{N}$ as the proportion that behavioral effect takes in the population.

Solution and Interpretation. We only consider symmetric[6] pure strategy subgame-perfect equilibria. And now we provide three propositions to present and analyze the general form of solution of both the base model and the behavioral model.

Proposition 1: There exists a $\overline{K}$ such that the symmetric pure strategy subgame-perfect equilibrium set of the base model is given by $\{$Everyone chooses to chase at stage $k < K$, exits at stage K and behaves arbitrarily after that. For all $K < \overline{K}\}$.

Remark 1: Proofs of propositions have not been completed, and therefore we drop them out of this proposal.

The solution of the base model exhibited here manifestly presents one of the collective action dilemmas, the coordination problem occurring in multi-equilibrium game. In stock market, this corresponds to the difficulty of making right judgment on when the market-chasing will stop and a plunge follow. The hardness of this kind of coordination is overt, since making efficient contact with other players is costly, and when full commitment cannot be reached thus any contract cannot be self-enforced, the severity will be exacerbated. However, we will see the significant coordination efficacy of heuristic factor from the two propositions below.

Before presenting the propositions, we denote $K^* = [\frac{P^* - Ne_0}{Ne_1}]$ to be the stage when P^* will be reached if all investors chase price before it. Furthermore, we assume that $\overline{K}$ is comparatively large so that $K^* < \overline{K}$, which can be done by selecting a β close to 1.

Proposition 2: There exist K_1 and K_2 such that $0 \leq K_1 \leq K^* \leq K_2 \leq \overline{K}$, and the symmetric pure strategy subgame-perfect equilibrium set of the $N - M$ rational players in behavioral model is given by $\{$Everyone chases at stage $k < K$, exits at stage K, and behaves arbitrarily after that. For all $K \in A \subset [K_1, K_1 + 1, ..., K_2]\}$

[6]We only include symmetric outcomes not for simplicity, but because asymmetric ones are unreasonable in such a symmetric setting and also are so many that each of them cannot bring meaningful insight.

Proposition 3: K_1 and K_2 can be written as functions with respect to $\theta = \frac{M}{N}$, and they are all monotonous functions. Specifically, $K_1(\theta)$ is increasing with range from 0 to K^* as θ varies from 0 toward 1, while $K_2(\theta)$ is decreasing with range from $\overline{K}$ downward to K^* as θ varies from 0 toward 1. And as for the second order variation pattern, we have $K_1(\theta)$ to be concave while $K_2(\theta)$ to be convex.

Astonishingly, the exogenous irrational behavioral belief about round number shapes a *equilibrium window* that rationality has to obey. The equilibrium window is described by a narrowed interval $W = [K_1, K_2]$ that contains the round number point K^*. And more importantly according to the second order property provided by Proposition 3, the speed of shrinking of interval W is faster when θ is small, and this implies that even with a relatively low θ interval W can be rather narrow. In other words, even if there only exists a comparatively small population that hold the same behavioral heuristics, the chaotic rationality can be efficiently coordinated.

What's more, from huge amount of empirical evidence, we can regard the round number effect very common and robust, for it sustains spanning long-term time variance and among different asset markets in different countries. This can be explained by the self-reinforcing characteristic of realized behavioral heuristics, that is, as we mentioned at the beginning of this section: now that the realized coordination is itself an equilibrium, which means in this outcome everyone reaches rationality, collective action remains stable with coordination repeated, equilibrium learned and the original heuristics reinforced. And through the model we elaborated, this logic can be construed with affirmative.

III. Empirical Design

To identify the round-number effect with reasonable accuracy, a cursory glance at market-scale data will not suffice. Stock market fluctuates with dozens of economic and non-economic variables. The observed round-number effect may indeed be driven by forces other than the behavioral equilibrium heuristics proposed in Section I. In this section we identify the round number effect for individual stocks with rigorous empirical models. Note that as our theory suggests, the behavioral equilibrium that takes round numbers as focal point materializes in the context of investors chasing the market with little consideration of stock fundamentals. Narrowing down the scope of analysis to individual stocks allows us to control for firm-level variables as well as the unobserved firm-specific characteristics that are time-invariant. The real round-number effect will be identified with greater precision once most confounding factors are removed.

Data. Our main data source is Tushare, a utility for crawling historical data of Chinese stocks. The source contains daily data of CSI 300 Index (Hushen 300 Index) from October 2005 to present with gaps. We have selected CSI 300 Index as our object of study since its the most popular market index Chinese investors normally refer to. Information of individual stocks, including opening price, closing price, pre-closing price, highest and lowest price of each trading day, buying volume, selling volume, total trade volume and the total shares possessed by top ten shareholders are also provided.

Baseline Model. We estimate the following model to identify the round-number effect at individual stock level.

$$\begin{aligned}\Delta Y_{it} =& \alpha_1 up_t + \alpha_2 W_t + \alpha_3 up_t * W_t \\ &+ \sum_{\tau=1}^{T} \kappa_\tau \Delta Y_{i,t-\tau} + X_{it}\beta + \gamma_1 \Delta HS_t \\ &+ \gamma_2 HS_t + \lambda_i + \varepsilon_{it}\end{aligned} \tag{1}$$

ΔY_{it} denotes the difference between selling volume and buying volume of stock i in trading day t. Large (and positive) value of ΔY implies that there are much more investors who are willing to sell the stock than investors who are willing to purchase, and vice versa. In the context of market chasing, large (and positive) value of ΔY_{it} reflects widespread belief among investors of stock i that quitting at time t is of their best interest, leading to what is perceived as a coordinated equilibrium of quitting. Note that when the behavioral equilibrium heuristic is at work, selling volume exceeds buying volume to such a large extent that only a very limited number of transactions will happen. Thus there is roughly a negative relationship between ΔY and total trade volume. up_t is a binary variable that indicates situations of market chasing. It takes the value of one when the closing value of stock index at day t is greater than that of $t - S$, and over 90% of the S trading days prior to day t experienced a rise in stock index. For convenience, we define a notation $R_{t,S} = \left\{ \frac{1}{S} \sum_{s=0}^{S} I\left[\Delta HS_{t-s} > 0\right] \right\} * I\left[HS_t > HS_s\right]$, which represents the proportion of rise from day $t - S$ to day t. W_t is an indicator of equilibrium window. It takes the value of one when the closing value of stock index falls into a narrow interval surrounding a round number (e.g. 3000). Then we provide the mathematical definitions of up_t and W_t are given below

$$up_t = \begin{cases} 1, & R_{t,S} > 0.9 \\ 0, & otherwise \end{cases} \tag{2}$$

$$W_t = \begin{cases} 1, & |HS_t - 1000 * [HS_t/1000]| > \overline{W} \\ 0, & otherwise \end{cases} \tag{3}$$

Our main independent variable of interest is the interaction of up_t and W_t, which takes the value of one if and only if the stock index falls into the equilibrium window during market chasing. As our theoretical model predicts, the parameter associated with this interaction term should take positive value, i.e. a coordinated equilibrium that investors collectively quit the market chase appears as stock index reaches the focal point of round numbers. X_{it} denotes firm fundamentals that affect market demand for its stocks. Closing value of CSI 300 Index at trading day t HS_t and its change relative to its previous day value ΔHS_t are also controlled for. Stock-fixed effect are added to control for the unobserved heterogeneity across individual stocks. Finally, lagged values of dependent variable is included to account for a large promotion of variation of ΔY_{it}.

Baseline Results. Using the data we have collected up to the day this proposal is written, we perform a linear regression to identify the round-number effect. Note that there are two major differences between the model estimated in this subsection and the full specification of our baseline model. First, due to data limitation, we replace the dependent variable ΔY with trade volume. Since as discussed earlier, there is a roughly negative relationship between total trade volume and the difference between selling and buying volume, the former makes an imperfect yet plausible alternative for the latter. Second, we havent matched the stock data with firm data so firm fundamentals that vary across time are not yet controlled for. However we are able to control for unobserved heterogeneity across stocks thats time-invariant using fixed effect model. Note that since the lagged value of dependent variable may be correlated with the error term due to serial correlation, the model is estimated using both ordinary least square (OLS) and two-stage least square (2SLS).

(Table I. Please see appendix.)

Table I lists the parameter estimates of W_t where different lengths of equilibrium window ($\overline{W}$) are chosen and different criteria (values of S) of market chasing are applied. Consistent with the prediction of our theoretical model, the results suggest a robust and negative correlation between trade volume and being within the equilibrium window, lending evidence, though tentative, to the existence of round-number effects and behavioral equilibrium heuristics. At least it is safe to conclude that the behavioral pattern of market-chasing investors changes substantively as stock market index reaches round numbers, which in turn is reflected in the substantial decrease in total trade volume.

Extensions. In addition to the behavioral heuristics proposed in the theoretical model, other complementary efforts of coordination may be observed as stock index approaches the focal point of coordinated equilibrium. One possible channel of coordination is through commenting on online stock forum. Identifying this channel will lend more evidence to the behavioral equilibrium heuristics as the explanation for round-number effect. To achieve this, we first obtain comments and posts for each stock in our sample from online forums and count the frequency of round-number-related posts (e.g. $themarketisapproaching 3000, youneedtoselloutquick$) in every trading day. Then we reestimate the baseline model, with the frequency of round-number-related posts $Post_{it}$ as the dependent variable in lieu of ΔY. The rest of the equation remain the same. The model is given below.

$$\begin{aligned} Post_{it} =& \alpha_1 up_t + \alpha_2 W_t + \alpha_3 up_t * W_t \\ &+ \sum_{\tau=1}^{T} \kappa_\tau Post_{i,t-\tau} + X_{it}\beta + \gamma_1 \Delta HS_t \\ &+ \gamma_2 HS_t + \lambda_i + \varepsilon_{it} \end{aligned} \tag{4}$$

Moreover, the equilibrium heuristics that take round numbers as focal points presuppose the existence (and then the belief among rational traders of such existence) of irrational traders who unconditionally choose to sell out their share once market index reaches round numbers. As $Proposition 3$ suggests, the larger the proportion of irrational traders with strong inclination to round numbers is among all investors, the faster the market-chasing game converges to the equilibrium window. To substantiate the claim, we propose to study the relationship between the degree of round-number effect for each individual stock and its shareholder structure. Firstly, we reestimate the baseline model using seemingly uncorrelated regression and obtain the parameter estimate (with confidence interval) of the interaction term $up_t * W_t$ for each individual stock[7]. The model for SUR estimation is given below.

$$\begin{aligned} \Delta Y_{it} =& \alpha_{i1} up_t + \alpha_{i2} W_t + \alpha_{i3} up_t * W_t \\ &+ \sum_{\tau=1}^{T} \kappa_{i\tau} \Delta Y_{i,t-\tau} + X_{it}\beta_i + \gamma_{i1} \Delta HS_t \\ &+ \gamma_2 HS_{it} + \varepsilon_{it}, \quad i = 1, \ldots, N \end{aligned} \tag{5}$$

As a second step, we construct an indicator of shareholder structure based on the information crawled via $Tushare$. For instance, the total share possessed by the top 10 stock holders of each individual stock reveals valuable information of shareholder structure: larger value of total share implies that specialized investors and investing groups hold disproportionately more shares than individual investors and non-professionals, whereas smaller value indicates otherwise. Since both conventional wisdom and existing literature suggest that professionals are less likely to engage in irrational market behavior, we expect stocks whose holders are large-scale professional traders are less affected by round number effect. Finally, we plot the parameter estimates (and confidence 95% interval) of the interaction term (i.e. a measure of how strong the round-number effect is) for all individual stocks, against the total share possessed by their top 10 shareholders or other indicator for shareholder structure. If $Proposition 3$ stands true, the scatterplot will look like a curve with negative slope. Moreover, we expect to see the parameter estimates converge to zero as total shares converge to one, i.e we expect the round number effect to diminish as more of the stock is held by large professional investors. An illustration is given by Figure I. Note that this illustration is based on simulation instead of real data.

[7]for reasons of endogeneity related to lagged dependent variable, the model is estimated using three-stage least square (3SLS) and full information maximum likelihood (FIML) as well.

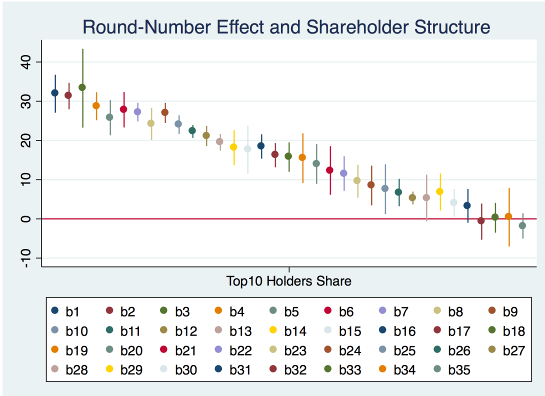

Fig. 1: Figure I

IV. Conclusion and Prospect

In this paper we examine how behavioral heuristics narrows equilibrium set in collective coordination problem, with empirical recognition using data from China stock market. We concludes that the appearance of market slump after a chasing is decided by the proportion of irrational investors and their realized behavioral heuristics. Controlling for other factors, the trade volume would increase when the stock indices approaches round numbers, which reflects the outcome of coordination in the process of market chasing.

We are now halfway to finish the whole paper mainly for lack of sufficient data on the details of asking prices and volumes. Moreover, the robustness of our theory is remained to be checked with prices in other asset markets. Later on we are going to work on the data problem and inspect deeper into our framework.

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APPENDIX

Table I. Baseline Specification: Round-Number Effect

	Dependent Variable = Volume							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Window (+10)	-23,618*** (1,812)	-13,334*** (972.6)	-4,014*** (992.8)		-7,692*** (1,119)			
Window (±20)	-18,240*** (1,145)	-20,207*** (1,439)	-26,752*** (1,926)	-54,509*** (4,118)	-14,075*** (1,264)	-21,805*** (1,721)	-32,067*** (2,356)	-54,509*** (4,118)
Window (±30)	-16,638*** (956.1)	-20,207*** (1,439)	-26,752*** (1,926)	-54,509*** (4,118)	-12,579*** (1,083)	-21,805*** (1,721)	-32,067*** (2,356)	-54,509*** (4,118)
Window (±50)	-2,316*** (487.7)	-17,761*** (1,257)	-20,886*** (1,584)	-26,023*** (2,201)	-2,324*** (542.6)	-18,555*** (1,440)	-23,950*** (1,857)	-26,023*** (2,201)
Window (±100)	3,883*** (406.5)	4,826*** (676.1)	-3,671*** (537.8)	-7,369*** (1,203)	3,341*** (494.1)	-91.44 (671.3)	-8,130*** (624.3)	-11,977*** (1,416)
Observations	5,140,211	3,654,524	3,654,524	2,292,487	5,140,211	3,654,524	3,654,524	2,292,487
R-squared	0.757	0.772			0.757	0.772		
Estimation	OLS	OLS	2SLS	2SLS	OLS	OLS	2SLS	2SLS
Time Span	10 Days	10 Days	10 Days	10 Days	20 Days	20 Days	20 Days	20 Days
Lagged DV	1	2	1	2	1	2	1	2
Stock FE	√	√	√	√	√	√	√	√

***NOTE*:** Robust standard errors clustered at individual stocks. * significant at 10% level, ** 5%, *** 1%.

Fig. 2: Table I