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1 Introduction

Financial markets are commonly modeled by a set of independent actors who combine public and private information in order to make investments. Public information is, as the name suggest, available to all decision-makers and private information is unique to each. A minimum of information sharing is expected, perhaps inferred by analyzing an individual's past spending, but for the most part private information remains so. At no point does all private information become public, creating an even playing field where rational agents will make identical decisions. The market is always characterized by information asymmetries.

These models carry the assumption that individuals' choices are strongly guided by their private information. The publicly known data is what prevents them from making poor decisions, keeping them updated with how market action has changed the dynamics of the system. Private information, on the other hand, gives investors an edge, helping them make a decision that is more likely to succeed against competing strategies. Wherever it applies, one expects players to make choices based upon their private data, rather than the publicly known information.

However, this assumption has been contradicted by empirical studies. Numerous studies have found that investors do not always act as individuals, guided by private information, but rather exhibit a tendency for collective action. Investors, in practice, herd. Cont and Bouchad (1992) cite evidence of herding among fund managers and financial analysts in domestic markets [3, 174]. Bikhchandani and Sharma (2000) present similar evidence from data in emerging Eastern markets [1]. Herding, the phenomena where all or most actors in the market converge upon a single decision, occurs much more often than we might naively expect.

Reasons for herding are myraid, and will not be discussed here. Additionally, we elide discussion of the outcomes of herding. The natural assumption is that herding is irrational, a poor strategy compared to using private information; however, there are a number of scenarios where herding becomes the optimal strategy. Here, we concern ourselves only with modeling herd behavior. Whether the decision was rational, profitable, or otherwise, is not important here. We only seek to identify whether a decision was the product of herding or not, and to predict when herding will guide other choices. In particular, we analyze the manner in which previous studies have characterized herding, note where they have succeed, and identify where they may be improved. Our focus is on the analysis of herding models.

2 Background

Our approach in choosing papers to read for this topic was to find one established, canonical paper that has had a significant influence on future works, and a newer paper offering modern insight and a more refined model. From the former, we sought a summary of the phenomena and problem and an intuitive, uncluttered model upon which to test data. We hoped this model would give a simple measure on one or two dimensions, to provide firm ground on which to build more intricate experiments. Then from the latter paper, we wanted a more focused effort into solving a particular problem, to give an indication of which open questions remain pertinent today. We expected the model in the newer paper to be more intricate, better tailored to answering a particular question or analyzing a particular structure of market as opposed to the more general, canonical model.

To this end we have read Cont and Bouchad (2000), which presents a simple randomized model for herding, and Boorz et. al. (2013), which critiques the current state of research and applies herding techniques to high-frequency data. For additional background we reference Bikhchandani and Sharma (2001), an IMF paper which summarized the phenomena and provided empirical data on herding in emerging markets, and a few other related works.

3 Review of Cont & Bouchaud

3.1 Summary

Cont and Bouchad (2000) did not set out to study herding per se, but rather to explain a curious observation. Empirical data on the distributions of stock prices and returns had unexpectedly fat tails [3]. Although these tails were caused by large fluctuations in prices, but the cause of the fluctuations was unknown. Prior work by Cutler (1989) and Shiller (1989) had established that the arrival of information or variations in fundamental economic variables did not always relate to heavy-tailed distributions, which led the authors to hypothesize that herding might be a cause. Thus they developed a new herding model with the hope that its underlying distribution would match those found in the data.

Before presenting their model, the authors summarize previous models and how those models guided the present design. One problem they wanted to avoid was the assumption that decisions take place sequentially. A natural herding model, proposed by Bikhchandi (1992) has investors take turns making decisions based off the state of the market and competitors' past actions. While easy to understand, this type of model is not realistic. Stock markets are not characterized by sequential actions. However, an earlier non-sequential model by Orlèan (1995) proved insufficient because it gave all players an equal likelihood of copying one another. Thus the authors' model addresses is not sequential and uses a randomized communication structure.

Another issue is the intricacy of the model. The authors critique earlier work by Bat (1997) for being too complex, for having so many parameters that determining causation was difficult and comparison against empirical data was overly tedious and had too many of failure [3]. Hence their model is simple and uncluttered: a set of N agents choose to buy, sell, or hold a single asset. At the start of the simulation, agents are formed into groups by creating edges with probability c/N for some connectivity parameter $c \in [0, 1]$. These clusters are the herds for the rest of the simulation, which is then executed, logging returns throughout.

3.2 Main Technical Content

The formalization of a randomized herding model and its corresponding analysis constitute the main technical content of this work. The authors identified problems with past approaches and addressed these in their model. The analysis presented here is detailed and comprehensive, offering convincing evidence that the model does indeed give heavy-tailed distributions much like those observed empirically.

3.3 Relation to coursework

This paper, indeed this topic, brings together a variety of topics from this course. Concepts dealt with explicitly in this paper are random graphs and game-theoretic models. Indeed, what sets this model apart from its contemporaries is that it was randomized, which was ultimately a better technique for dealing with trading networks. Information cascades are addressed here as well, though they are not the core focus. It is assumed, at this point in the literature, that information cascades cause herding. This model challenges that assumption slightly by rejecting sequential models of herding, but it is not for another decade that the legitimacy of the search cascade hypothesis is seriously questioned [4].

3.4 Weaknesses

3.5 Questions

4 Review of Boortz et. al.

4.1 Summary

Boortz et. al. summarizes the recent efforts of a group of German researchers towards linking the empirical and theoretical perspectives of herding. Research on herding, they claim, has been divided for too long into two separate empirical and theoretical realms. Theoreticians have developed models in line with the evolution of modern securities markets; as the pace and style of trading has changed, so have the models. However, these models are not applicable to the corresponding empirical context. The cause here is that researchers do not rigorously test the models against real data. Why? Because they fail to obtain quality data.[1] In fact the search for legitimate, detailed data is a pervasive issue. Empirical studies occur wherever a fine source is found, but the majority have had to compensate by studying aggregates over relatively large blocks of time. Depending on the data available, published results have developed from conclusions based on weekly or even yearly aggregates.[2] Granted, this may be appropriate for slow moving, established markets, but it is certainly not accurate for high-frequency or emerging markets. Markets in which millions of trades occur every second demand more granular measurements than by day or by week. Thus we have one issue: that theoretical and practical results are not synchronized.

The authors seek to address this crucial discontinuity by giving theoretical and empirical results within the same paper. First, they present a dynamic model for measuring the intensity of herding in a fast-paced market. Next they run this model on simulated data and generate two hypotheses. Finally, they test these hypothesis on up-to-date and relevant market data, recorded during the 2007 financial crisis and provided by the German Federal Financial Supervisory Authority [2, 3]. The output here is used to validate the hypothesis, and then the authors present their conclusions.

4.2 Main Technical Content

The definition and rigorous application of a herding measure for high-frequency data are the main contributions of this work. Although their model is but a slight modification of one developed by Park and Sabourian (2007), using only a less restrictive definition of when herding has occurred, it is still a useful contribution. This usefulness is affirmed in the model's application to the simulated and actual data: it developed two hypothesis which, when applied to market data, were found to describe the observations most of the time.

4.3 Herding Measure

Interestingly, the model used here is simple, operating on very few parameters. Only one asset is traded between buyers and sellers, and investors are either bucketed into two groups: informed and noisy [2, 5]. Noisy traders randomly buy a stock at each opportunity. Informed traders make decisions based on the past and current state of the market, have the choice of buying or holding at each opportunity, and are evaluated against a few criteria to determine whether they have exhibited herd behavior. We repeat here the criterion for a trader to herd as a buyer:

- The trader is informed
- The trader chooses to buy at the current time

[1] Certainly this was a problem we faced in writing this reaction piece. Data of poor quality was available for sale or signup, but high-quality, high-frequency data took a great deal of effort to acquire.

[2] Here "aggregates" should be taken to mean the window over which data are compared.

- The trader either sold or did not act at the previous time
- The number of buyers currently in the market exceeds the number of sellers (informed or otherwise)

Yet the usefulness and applicability of the model stems from its simplicity. As noted in the authors' introduction, theoretical models had become advanced and multi-faceted, but in doing so had grown apart from contemporary empirical work.

4.4 Relation to coursework

Like the previous work, this paper discusses information cascades, simple game theoretic models, and randomized networks. These concepts join to create a model suitable for analying complex, real-world transactions.

4.5 Weaknesses

4.6 Questions

5 Proposal

High-frequency trading is a relatively new phenomena, but has revolutionized financial markets. Since its emergence during the last decade, high-frequency trading has revolutionized commodities markets. The modern trading floor is much different from the one analyzed by Cont and Bouchad. To this end, we need a new model of herding corresponding to the new model of transactions. We list the following criteria for herding models:

- idk
- ???

Note that the Boortz model fails TODO, and Cont and Bouchad model fails TODO.

6 Discussion

We have thus far considered herding the irrational, or at least unexpected behavior, assuming that investors follow their private information as the norm and degenerate into the herd mentality in exenuating circumstances. Indeed, this is the the viewpoint contemporary models have embraced: herding is measured as deviation from some expected investment strategy, identified by similarity across different parties. One wonders whether this is a valid assumption. Making decisions based off the actions of fellow investors is not so far removed from making decisions based on publicly available information. Historical trends, which are in effect what herd participants follow when making their decisions, are simply another form of public information. The herd mentality is more or less what we would expect to see in a completely fair market, without any information asymmetries. We might then refine the initial question to assume that herding will occur and instead ask how significant a role market trends play in investors' decision-making—if the herd action exerts a disproportionately large influence on buyer and seller behavior—but it seems strange, on review, to assume that players are not greatly influenced by their competitors actions.

Perhaps a better phemonena to explore are the circumstances in which an investor ignores *public* information and instead follows private knowledge or intuition. A contrary model, which instead of tracking similarity measures differences between investors, might provide more insight to the workings of these markets. Assuming that investors follow the public information and each others' decisions exclusively might permit us to draw conclusions about the influence or extent of participants' private information. This is a naive investment strategy, subject to gaming and easily misled, but may in fact be a better generalization for how investors function in practice.

7 Conclusion

We have identified the topic of herding behavior in financial markets as a subject of interest, read a number of papers concerning this phenomena, and presented our findings and extensions here. In particular, we summarized Cont and Bouchad (2000), which provided a highly influential randomized model of commodities markets where herding occurs, and Boortz et. al., which sought to reconcile the research to date via a straightforward model tested on high-frequency data. What remains to be done, in our opinion, is to test a more intricate model on high-frequency data. Hence a possible avenue for our future research is to acquire high-frequency transaction data and run a new model on it.

References

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