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Why is equity order flow so persistent?

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ABSTRACT

Order flow in equity markets is remarkably persistent in the sense that order signs (to buy or sell) are positively autocorrelated out to time lags of tens of thousands of orders, corresponding to many days. Two possible explanations are herding, corresponding to positive correlation in the behavior of different investors, or order splitting, corresponding to positive autocorrelation in the behavior of single investors. We investigate this using order flow data from the London Stock Exchange for which we have membership identifiers. By formulating models for herding and order splitting, as well as models for brokerage choice, we are able to overcome the distortion introduced by brokerage. On timescales of less than a few hours the persistence of order flow is overwhelmingly due to splitting rather than herding. We also study the properties of brokerage order flow and show that it is remarkably consistent both cross-sectionally and longitudinally.

1. Introduction

Order flow in equity markets, defined as the process assuming value one for buyer initiated trades and minus one for seller initiated trades, is persistent in the sense that orders to buy tend to be followed by more orders to buy and orders to sell tend to be followed by more orders to sell. Positive serial autocorrelation for the first autocorrelation of order flow has been observed in many different markets.[1] In fact, order flow is *remarkably persistent*: As illustrated in Fig. 1, all the coefficients of the autocorrelation function of signed order flow are positive out to large lags, corresponding in trade time to

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[1] Positive autocorrelation for a single lag was observed in the Paris Bourse by Biais et al. (1995), in foreign exchange markets by Danielsson and Payne (2012), and in the NYSE by Ellul et al. (2007) and Yeo (2008). See also Chordia et al. (2002) and Chordia et al. (2005).

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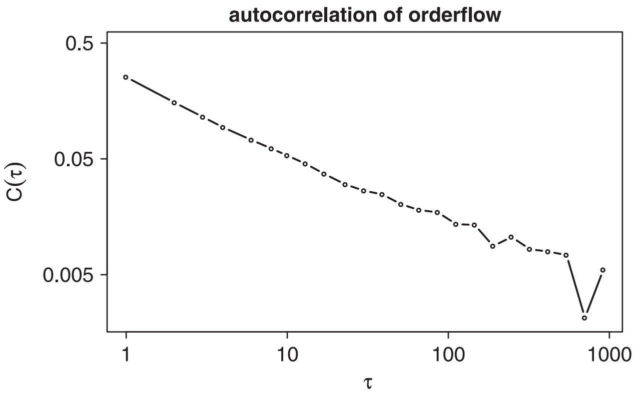

Fig. 1. Autocorrelation function of order flow for the stock AZN in the first half of 2009, plotted on double logarithmic scale. The time lag τ is measured in terms of number of effective market order placements, where an effective market order is any order that results in an immediate transaction. To reduce estimation error we use order signs rather than order size and individual autocorrelations are binned for large lags. The results are similar if we use order volume.

tens of thousands of transactions or in real time to many days.[2] This is highly consistent across different markets, stocks, and time periods.

In this paper we perform an empirical study to elucidate the cause of this remarkable persistence. This study is based on a unique data set from the London Stock Exchange (LSE) with codes indicating the exchange member who executed each order. Members of the exchange may trade for their own accounts, but they may also act as brokers for investors who are not members of the exchange.[3] As we will argue here, this provides useful information about the patterns of behavior of investors,[4] even if it falls short of the fine grained data on the identity of investors that would make the results unequivocal.

Our goal here is to distinguish between two fundamentally different types of behavior, order splitting and herding. Order splitting occurs when single investors split desired large trades into smaller pieces and execute them gradually. Our results here add to earlier evidence that order splitting is an important effect. The strategic motivations for order splitting were originally derived by Kyle (1985), who showed that an informed trader with a monopoly on private information would trade gradually in order to reduce impact. Early empirical studies by Chan and Lakonishok (1993) and Chan and Lakonishok (1995) using brokerage data with information about investors showed that order splitting is widespread. Chordia et al. (2002, 2005) found that daily order imbalances are serially autocorrelated and highly persistent,[5] and pointed out that they can be caused either by order splitting or herding. Lillo et al. (2005) introduced a model for order splitting connecting the size of large orders with the autocorrelation of order flow and showed that its predictions gave good agreement with data from the London Stock Exchange. Gerig (2007) demonstrated that for the LSE stock AZN the trades coming from the same brokerage have long-memory, whereas trades from different brokerages do not (see also Bouchaud et al. (2009)). Vaglica et al. (2008) reconstructed the size of large orders from brokerage data and found that it is distributed as predicted by Lillo, Mike and Farmer.

An alternate hypothesis is that the extreme persistence of order flow is due to herding, as proposed by LeBaron and Yamamoto (2007), LeBaron and Yamamoto (2008), who constructed an agent-based model of imitation that produces highly persistent order flow. There is a large literature on herding and its existence in equity trading at longer timescales is well-documented.[6] There are many strategic reasons why agents might herd, including reputational considerations, delayed response to public information, slow diffusion of private information, or imitation based on inferring the private information of others.

Thus there are good arguments that one should expect both order splitting and herding. Here we study the London Stock Exchange to quantitatively estimate their relative importance at short timescales, and in particular the extent to which these

[2] The extreme persistence of order flow was independently pointed out by Bouchaud et al. (2004) and Lillo and Farmer (2004). In fact order flow is so persistent that it is a long-memory process, i.e. its autocorrelation function is non-integrable Beran (1994). This has been shown for the London and New York stock exchanges by Lillo and Farmer (2004), for the Paris stock exchange by Bouchaud et al. (2004) and for the Spanish stock exchange by Vaglica et al. (2008) and Moro et al. (2009). Note that Axioglou and Skouras (2011) argue that order flow is much more persistent within a given day than across successive days. None of our results here depend on long-memory; we mention this only to emphasize the extreme persistence of order flow.

[3] We often use the terms “member” and “broker” interchangeably.

[4] By *investor* we mean any trading entity with a coherent trading strategy. This could correspond to a specific trading account within an institution such as an investment bank or hedge fund, or a private individual trading for his or her own account.

[5] Order imbalance for each stock over any time interval is typically calculated using the difference in the number of buy market orders and sell market orders, or the difference in the dollar value from buy market orders and sell market orders. Variations of this metric can use either a scaling factor or calculating a ratio instead of a difference. Brown et al. (1997), Chordia et al. (2002), Chordia and Subrahmanyam (2004), Chordia et al. (2005), Lo and Coggins (2006), and Boehmer and Wu (2008) found correlation between order imbalance and returns, however, the evidences are not consistent on the direction of causality. Looking at 5 min order imbalances, Chordia et al. (2008) have found that return predictability has declined over time.

[6] See for example Scharfstein and Stein (1990), Lakonishok et al. (1992), Banerjee (1992, 1993), Bikhchandani et al. (1992), Hirshleifer et al. (1994), Orlean (1995), Raafat et al. (2009), and Barber et al. (2009). Several previous studies have focused on the effect of communication network structure on price fluctuations; (see Kirman and Teyssiere, 2002; Iori, 2002; Cont and Bouchaud, 2000; Tedeschi et al., 2009). Lakonishok et al. (1992) and Wermers (1999) find only weak evidence for herding.