Finance Research Letters 000 (2016) 1–7

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

Market microstructure during financial crisis: Dynamics of informed and heuristic-driven trading

Mihály Ormos*, Dusán Timotity

Department of Finance, Budapest University of Technology and Economics, Magyar tudosok krt. 2., 1117 Budapest, Hungary

A R T I C L E I N F O

Article history:
Received 26 May 2016
Accepted 2 June 2016
Available online xxx

JEL codes:
D47
D53
D82
G02

Keywords:
Market microstructure
Heuristic-driven trader
Probability of informed trading
Probability of heuristic-driven trading
Contrarian trader
Size effect
Volume effect

A B S T R A C T

We implement a market microstructure model including informed, uninformed and heuristic-driven investors, which latter behave in line with loss-aversion and mental accounting. We show that the probability of informed trading (PIN) varies significantly during 2008. In contrast, the probability of heuristic-driven trading (PH) remains constant both before and after the collapse of Lehman Brothers. Cross-sectional analysis yields that, unlike PIN, PH is not sensitive to size and volume effects. We show that heuristic-driven traders are universally present in all market segments and their presence is constant over time. Furthermore, we find that heuristic-driven investors and informed traders are disjoint sets.

1. Introduction

Market microstructure has long been considered to influence asset pricing (Glosten and Milgrom, 1985; Kyle, 1985). One of the key points in this relationship lies in asymmetric allocation of information in capital markets contributing to the uncertainty around the investments of liquidity traders. Easley et al. (1996, 2002) capture this latter effect by introducing a novel measure, the probability of informed trading (PIN), and show its significant effect on the liquidity and the expected return of assets.

In this paper, we describe the dynamics of their proposed measure within a sample including highly volatile periods and structural shocks: we analyze the microstructural change during 2008 and take into consideration the structures of both the pre- and post-Lehman era. Our sample covers every executed trade made through Budapest Stock Exchange between 2 January 2008 and 31 December 2008.

Furthermore, we extend our analysis to another type of investors. According to Ormos and Timotity (2016a), due to loss-aversion and intertemporal mental accounting, investors tend to follow contrarian strategies: they invest into riskier (less risky) assets or increase (decrease) leverage subsequent to previous negative (positive) market shocks. We introduce this

* Corresponding author. Fax: +36 1 4632745.
E-mail addresses: ormos@finance.bme.hu (M. Ormos), timotity@finance.bme.hu (D. Timotity).

http://dx.doi.org/10.1016/j.frl.2016.06.003
1544-6123/

Please cite this article as: M. Ormos, D. Timotity, Market microstructure during financial crisis: Dynamics of informed and heuristic-driven trading, Finance Research Letters (2016), http://dx.doi.org/10.1016/j.frl.2016.06.003

latter pattern into market microstructure by including a class of heuristic-driven traders in the base model consisting of informed and uninformed traders and specialists. The relevance of such traders in market microstructural analysis is supported by numerous studies: according to Yao and Li (2013), prospect theory investors can behave as contrarian noise traders in a market. This is confirmed by Chordia et al. (2002), who find that order imbalance increases (decreases) subsequent to market declines (jumps), which indicates contrarian investors in aggregate. Furthermore, providing evidence for our particular explanation, Kadous et al. (2014) argue that investors act as contrarians only if they have held the particular asset in the past that they buy in the subsequent period.

In our empirical tests we find that, while the proportion of informed investors varies in time and amongst different assets, the probability of heuristic-driven trading (PH) is insensitive to temporal and cross-sectional factors. Therefore, we argue that the existence of heuristic-driven traders forms a universal and robust property of capital markets.

2. Data and methodology

In contrast to Glosten and Milgrom (1985) and Kyle (1985), where uninformed traders are defined as those who do not possess fundamental information on assets, irrespective of their motives, our setting is rather similar to the paper of Bloomfield et al. (2009), in which uninformed investors can have other trading motives than fundamental (e.g. behavioral). In particular, we argue that there exists a class of heuristic-driven trader that behaves in line with the contrarian investment pattern (i.e. buy/sells subsequent to losses/gains), which leads to a positive probability of such investors. We apply this probability (PH) as a defining measure of market microstructure.

This inclusion of PH in our microstructure model is based on the following idea by Ormos and Timotity (2016a): investors that are sensitive to loss-aversion and mental accounting, when they lose (gain) money, tend to aggregate in time, and therefore, their required return increases (decreases) in the subsequent period; then, this raised (lowered) expected return can be obtained by investing in riskier assets or increasing leverage, hence, their demand for risky assets increases (decreases). Altogether, therefore, this behavior leads to a negative relationship between order imbalance and previous market returns.

This pattern could also provide an explanation for recent findings on investors' portfolio choice, according to which high-aspiration investors (those with high required returns) trade more than the average (Magron, 2014). For example, if one invests in assets providing higher expected return with greater risk, unexpected deviations become larger; hence, the aforementioned pattern plays a more significant role in portfolio choice.

Our microstructural model is based on the following assumptions: (1) investors hold well-diversified portfolios; therefore, changes of the market portfolio is a proxy for their portfolio; (2) all stocks are risky assets; thus, subsequent to a market loss (gain), investors increase (decrease) their portfolio risk and expected return through leverage in the market portfolio, which yields a higher (lower) demand for individual stocks; (3) orders from heuristic-driven buyers have Poisson distribution and arrive at rate $\epsilon_b^H \max(0, -I_{t-1})$, while order from heuristic-driven sellers arrive at rate $\epsilon_s^H \max(0, I_{t-1})$, where I_{t-1} stands for an indicator function of

$$I_{t-1} = \begin{cases} 1 \; if \; r_{t-1}^M \geq 0 \\ -1 \; if \; r_{t-1}^M < 0 \end{cases},$$

in which r_{t-1}^M stands for the previous market return. Since we use the daily number of buy and sell transactions in PIN estimations, the length of the previous market shock is also set to one day (thus, I_{t-1} is the function of the return of the preceding day). This is in line with the empirical findings on the inititally strong, yet fading property of anchoring to previous returns (Ormos and Timotity, 2016b). The intuition behind this latter assumption is defined by the contrarian pattern discussed above, which aims to capture the increased number of buy (sell) orders subsequent to market losses (gains).

This asymmetric framework is in line with recent studies on the relationship between the market return and future trading volume: according to Dodonova (2015), extreme negative market returns lead to high future trading volume, while extreme positive returns have only a slight effect on future volume. Our second assumption is also supported by an extensive amount of results on the hedging role of government bonds in portfolio diversification, which is especially relevant in highly volatile periods (Acosta-González et al., 2016).

Apart from the aforementioned, we apply a set of parameters similar to Easley et al. (1996, 2002): private information emerges each day with probability α, which contains bad and good news with probabilities δ and (1-δ) respectively. Orders from uninformed buyers and sellers arrive at rate ϵ_b and ϵ_s, while informed orders arrive at rate μ if the private information event has occurred. B and S represent total buy trades and sell trades for the day respectively. Then, the likelihood function of the parameter set θ for a single day is given by:

$$\begin{aligned} L(\theta|B, S, I_{t-1}) \\ = (1-\alpha) e^{-\left[\epsilon_b + \epsilon_b^H \max(0, -I_{t-1})\right]} \frac{\left[\epsilon_b + \epsilon_b^H \max(0, -I_{t-1})\right]^B}{B!} e^{-\left[\epsilon_s + \epsilon_s^H \max(0, I_{t-1})\right]} \frac{\left[\epsilon_s + \epsilon_s^H \max(0, I_{t-1})\right]^S}{S!} \\ + \alpha\delta e^{-\left[\epsilon_b + \epsilon_b^H \max(0, -I_{t-1})\right]} \frac{\left[\epsilon_b + \epsilon_b^H \max(0, -I_{t-1})\right]^B}{B!} e^{-\left[\mu + \epsilon_s + \epsilon_s^H \max(0, I_{t-1})\right]} \frac{\left[\mu + \epsilon_s + \epsilon_s^H \max(0, I_{t-1})\right]^S}{S!} \end{aligned}$$

Please cite this article as: M. Ormos, D. Timotity, Market microstructure during financial crisis: Dynamics of informed and heuristic-driven trading, Finance Research Letters (2016), http://dx.doi.org/10.1016/j.frl.2016.06.003