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Full Length Article

Liquidity flows, drawdowns and trading networks in order driven markets: An application to Borsa Istanbul

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Abstract

We empirically analyze the agent based relationship between liquidity flow and downside price formation based on the individual trading network topologies of 20 equities in Borsa Istanbul between 2009/01–2013/12. We apply PageRank Algorithm to extract daily centrality degree in liquidity demand of domestic financial institutions classified as informed traders and use intraday maximum drawdown to capture intraday liquidity shocks. We find evidence that 1) Maximum cumulative loss for a given day, deepens with the increasing liquidity demand of informed traders. 2) The uncertainty in the centrality degree of informed trading is overtime positively related with the uncertainty regarding the intraday maximum drawdown. 3) Time Patterns are significant: Drawdown depth is highest on Thursdays and lowest on Mondays. Highest (lowest) drawdowns on May (March) indicate the existence of Sell-in-May effect and earnings announcement effect, respectively.

JEL classification: C13; C33; D82; D85; G1; G32

Keywords: PageRank; Drawdown; Centrality; Liquidity; Information; Downside risk

1. Introduction

From the perspective of information theory, market consists of agents acting as sellers and buyers. These agents might hold differing or identical expectations on the underlying asset and filter any private or public information (i.e. signal) by observing the market price and trigger buy/sell orders if the prevailing price level meets their target strategies. As a consequence, underlying trading network topology is to greater extent shaped by the *liquidity flow* or *liquidity supply/demand structure* among these agents, which are in many studies clustered under different informational categories, such as informed traders vs. uninformed traders[1] or similarly as institutional (professional) vs. individual traders.[2] Moreover, technological development has been improving the trading mechanism in terms of speed and connectedness, causing markets and financial institutions behave more interdependent and connected than before. As a natural outcome, the link between liquidity risk and systemic risk arising from the underlying financial network became an interesting research area. On the other hand, regulatory authorities highly emphasize the importance of systemic risk by obligating financial institutions to increase their capital buffer by considering counterparties they are connected to.[3] Thus, recent financial events and resulted failures in traditional models led the market risk measurement to become a multidimensional process involving the underlying financial network topology.

Analyzing the behavior of market participants within a given trading topology and its influence on the market

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[1] Bagehot (1971), Copeland and Galai (1983), Easley and O'Hara (1987), Admati and Pfleiderer (1988), Glosten (1994), Huang and Stoll (1997), Chordia (2001), Shapira and Venezia (2001).

[2] Lakonishok et al. (1992), Shapira and Venezia (2001), Griffin et al. (2003).

[3] See Bank for International Settlement (BIS) Basel III Records.

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parameters is of great interest to this study, as to many others previously. If classifications for network participants exist, social network analysis (SNA) becomes a powerful tool for extracting necessary information from any complex data involving exchanges.[4] Majority of the studies related to financial networks mainly investigate the interbank markets. These markets exhibit relatively higher degree of information transparency and generally have smaller number of nodes (banks) when compared to that of stock markets.[5] Besides, studies dealing with stock/futures market networks are limited when compared to those investigating banking networks, mainly due to lower degree of market transparency as well as larger data size (e.g. number of nodes and edges) and relatively lower degree of economic importance of the underlying market.[6]

This study investigates the relationship between liquidity flow centrality and downside risk on a sample consisting of 20 selected equities of Borsa Istanbul (BIST) from different industrial areas between 2009/01 and 2013/12. Our main workflow is as follows: Firstly, we construct daily adjacency matrix (network) representing the liquidity flow from buy to sell side of for each stock, with respect to informational categories based on the buyer/seller types provided by the transaction data. Secondly, by applying PageRank algorithm (Brin & Page, 1998) we measure the centrality degree of the informed trading activity from the sell side of the trade book. Thirdly, we compute the daily maximum drawdown from intraday transaction prices. Lastly, we investigate the relationship between the centrality degree of the informed activity and daily maximum drawdowns by including asset and time specific effects. Our estimation results show that drawdowns deepens with the increasing liquidity demand of informed traders. Moreover, we report that time-fixed effects are highly significant over time: Drawdowns are relatively highest on Thursdays and lowest on Mondays. On May and March we observe on average the highest and lowest maximum drawdowns, respectively.

Our methodology is based on the similar motivation as of Hein, Schwind, and Spiwoks (2012) and Cole-Cohen, Kirilenko and Patacchini (2015) and provides a different perspective to analyze stylized facts in stock markets. In this manner, our contributions can be seen as an expansion to the existing empirical market microstructure, since the majority of previous studies concentrate on the evolution or topology of network measures before and after crisis/turbulence periods and they mainly focus on bank networks. Other than the tools that are provided by SNA, we also include intraday maximum drawdown to our model, which is until now not subject to the context that is relevant to our study. We use this measure to capture the largest cumulative loss per asset on any trading day and in this sense we are able to account for the downside risk and corresponding liquidity shocks that are often overlooked in the conventional market risk models focus on the change in daily close prices (e.g. Value at Risk) as an indicator.

This paper is organized as follows: Next section provides some necessary information about the market structure and design of Borsa Istanbul which is followed by the relevant literature research. Section 4 explains our methodology and finally, Section 5 and Section 6 are reserved for the findings and conclusions, respectively.

2. Market structure and design: Borsa Istanbul

Market structure and design depicts the organizational form of the market participants as a whole. Trading systems may differ both in terms of geographical location and infrastructure. For instance, in quote-driven OTC markets (e.g. NASDAQ), dealers -as intermediary agents-trade for their own inventory, whereby in brokerage (agency) markets (e.g. Tokyo Stock Exchange) only the brokers make transactions. Similarly, in an auction market (e.g. NYSE) there are no intermediary units except traders and in some order driven markets (e.g. BIST, Paris Bourse) traders may execute limit orders with the desired quantity and price. Moreover, there are trading systems that enable market makers (e.g. NASDAQ) and specialists (e.g. NYSE) to increase/decrease the market liquidity for a given stock. Additionally, in auction based markets traders transact on the market floor, whereby in some electronic markets such as NASDAQ and BIST, traders are not required to be at the market's physical location in order to submit/execute orders.[7] Thus, all these differences across market infrastructures leads to different market outcomes especially from the perspective of market participants. More importantly, recent findings suggest that the aforementioned discrepancies have influence on the tendency of foreign investors to invest in such markets which in return increase or decrease the additional liquidity supply in the market (Charitou & Panayides, 2009).

Market structure and design have various components such as the market type, rules regarding price discovery, trading times, transparency, order types, tick sizes etc. Market type, -being independent from the existence of the market maker- can be classified under the continuity and the degree of automation. In continuous markets, transactions can be realized with in the market opening and closing times, where as in periodic markets transactions can only be executed on the predetermined time points. On the other hand, in some markets, price formations can be dependent to prices realized in other markets which are set as benchmarks. Order types may also differ across markets due to different ruling mechanisms (e.g. limit, cancel, cancel-the-remaining, cancel-if-not realized

[4] Despite its advantages, availability/quality of data depending on the market transparency level is the major obstacle that SNA faces, especially when one deals with financial networks: Gathering data on interconnectedness of financial institutions or market participants is a challenging task depending mostly on the market transparency (here we leave OTC transactions aside).

[5] Boss et al. (2004); Soramäki et al. (2007); Saltoglu and Yenilmez (2010); Gabrieli (2011); Battiston et al. (2012); Kuzubas et al. (2014).

[6] Hein et al. (2012); Cole-Cohen et al. (2015).

[7] See Balogh and Koczan (2009) for further information about different market infrastructures.