MAGYAR TUDOMÁNYOS AKADÉMIA
Közgazdaság- és Regionális Tudományi Kutatóközpont

MTA KRTK KTI

Centre for Economic and Regional Studies
HUNGARIAN ACADEMY OF SCIENCES

MŰHELYTANULMÁNYOK DISCUSSION PAPERS

MT-DP – 2015/40

Price Impact and the Recovery of the Limit Order Book: Why Should We Care About Informed Liquidity Providers?

DÁNIEL HAVRAN – KATA VÁRADI

INSTITUTE OF ECONOMICS, CENTRE FOR ECONOMIC AND REGIONAL STUDIES,
HUNGARIAN ACADEMY OF SCIENCES BUDAPEST, 2015

Discussion papers
MT-DP – 2015/40

Institute of Economics, Centre for Economic and Regional Studies,
Hungarian Academy of Sciences

Price Impact and the Recovery of the Limit Order Book:
Why Should We Care About Informed Liquidity Providers?

Author:

Dániel Havran
research fellow
Institute of Economics - Centre for Economic and Regional Studies
Hungarian Academy of Sciences
e-mail: havran.daniel@krtk.mta.hu

Kata Váradi
assistant professor
Department of Finance
Corvinus University of Budapest
e-mail: kata.varadi@uni-corvinus.hu

August 2015

ISBN 978-615-5594-04-5
ISSN 1785 377X

Price Impact and the Recovery of the Limit Order Book: Why Should We Care About Informed Liquidity Providers?

Dániel Havran - Kata Váradi

Abstract

We examine the dynamics of the limit order book recovery in the purely order-driven markets. The configuration of the current limit placements in the order book determines the costs over the mid-quote for the buy and sell trades. By analyzing the relationship between the costs of the possible trades and market order-flows, we find that bid and ask side trade costs have significant impact on the direction of future market orders. Moreover, bid and ask side trade costs revert to their characteristic state. For the further analysis of limit order placement strategies, we extend the cost of trade approach by several attributes of the entire limit order book. Using snaphots about cost of round trip indicators from Budapest Stock Exchange stocks, we decompose the shape of the immediate price impact function to main three components, slope, convexity and hump-shape. By running impluse response simulations, we document the typical temporary movements of the trade costs curves and we find empirical evidences about the "pegging to the current mid-quote" behavior of the liquidity providers.

Keywords: market liquidity, resiliency, informed liquidity providers, immediate price impact function, order-driven market

JEL classification: C32, C51, G10, G17

Acknowledgements:

Dániel Havran is the participant of the Hungarian Academy of Science Postdoctoral Fellowship Programme.

This research was supported by the European Union and the State of Hungary, co-financed by the European Social Fund in the framework of TÁMOP 4.2.4. A/2-11-1-2012-0001 'National Excellence Program'.

The authors special thank for the Budapest Stock Exchange for the time-series data of the Budapest Liquidity Measure.

Árhatás és az ajánlati könyv visszatöltődése: Miért kell törődnünk az információval rendelkező limitajánlatokat adó kereskedőkkel?

Havran Dániel – Váradi Kata

Összefoglaló

A tanulmányban az ajánlati könyv visszatöltődésének dinamikáját vizsgáljuk a tisztán ajánlatvezérelt tőzsdéken. Egy piaci ajánlatot adó szereplő számára a vétel vagy az eladás középártól való eltérésének költségét a limitajánlatok elhelyezkedése adja meg. Ezeknek a kereskedési költségeknek, valamint az érkező piaci ajánlatok sorozatának kapcsolatát vizsgálva azt találjuk, hogy a kereskedés vételi és eladási oldali költségei jelentősen hatnak a jövőbeli piaci ajánlatok irányára. A kereskedés vételi és eladási oldali költségei átlaghoz visszahúzó folyamatot írnak le, amelyet a piaci tranzakciók térítenek ki egyensúlyi szintjükből. Az ajánlati könyves piac további elemzéséhez kiterjesztjük a kereskedési költségen alapuló megközelítést és az ajánlati könyv alakját több jellemző segítségével írjuk le. A Budapesti Értéktőzsde BLM-adatait felhasználva három tényezőre bontjuk a vételi és eladási azonnali árhatásfüggvényt: meredekségre, görbületre (konvexitás), valamint púposságra (ajánlatok helyi tömörülése). A becsült egyenletek alapján szimulált impulzusválasz függvényeket használva egy-egy tranzakció tipikus rövid és hosszú távú hatásait adjuk meg és írjuk le. A hosszú távú hatásokból levonható tanulság, hogy a limitajánlatokat adó (többnyire algoritmusokkal dolgozó) kereskedők folyamatosan a középárhoz igazítják ajánlatelhelyezési stratégiájukat, a piaci tranzakciók hosszú távon a könyv alakját nem, csak szintjét befolyásolják.

Tárgyszavak: piaci likviditás, rugalmasság, informált likviditásnyújtók, azonnal árhatás függvény, ajánlatvezérelt piac

JEL: C32, C51, G10, G17

Köszönetnyilvánítások:

Havran Dániel az Magyar Tudományos Akadémia 2013-as Posztdoktori Programjának ösztöndíjasa. A kutatás a TÁMOP 4.2.4. A/2-11-1-2012-0001 azonosító számú 'Nemzeti Kiválósági Program' projekt keretében zajlott. A projekt az Európai Unió támogatásával, az Európai Szociális Alap társfinanszírozásával valósul meg.

A szerzők köszönettel tartoznak a Budapesti Értéktőzsdének a Budapesti Likviditási Mutató idősoros adatbázisának a rendelkezésünkre bocsátásáért.

Price Impact and the Recovery of the Limit Order Book: Why Should We Care About Informed Liquidity Providers?

Dániel Havran*[1] and Kata Váradi†[2]

[1]Institute of Economics, Centre for Economic and Regional Studies, Hungarian Academy of Sciences

[1,2]Department of Finance, Corvinus University of Budapest

August, 2015

Abstract

We examine the dynamics of the limit order book recovery in the purely order-driven markets. The configuration of the current limit placements in the order book determines the costs over the mid-quote for the buy and sell trades. By analyzing the relationship between the costs of the possible trades and market order-flows, we find that bid and ask side trade costs have significant impact on the direction of future market orders. Moreover, bid and ask side trade costs revert to their characteristic state. For the further analysis of limit order placement strategies, we extend the cost of trade approach by several attributes of the entire limit order book. Using snaphots about cost of round trip indicators from Budapest Stock Exchange stocks, we decompose the shape of the immediate price impact function to main three components, slope, convexity and hump-shape. By running impluse response simulations, we document the typical temporary movements of the trade costs curves and we find empirical evidences about the "pegging to the current mid-quote" behavior of the liquidity providers.

JEL: C32, C51, G10, G17

Keywords: market liquidity, resiliency, informed liquidity providers, immediate price impact function, order-driven market

*The authors special thank for the Budapest Stock Exchange for the time-series data of the Budapest Liquidity Measure.

*Dániel Havran is the participant of the Hungarian Academy of Science Postdoctoral Fellowship Programme.

†This research was supported by the European Union and the State of Hungary, co-financed by the European Social Fund in the framework of TÁMOP 4.2.4. A/2-11-1-2012-0001 'National Excellence Program'.

1 Introduction

This study investigates the relationship between the limit order book structure and the market order flow. The structure of the limit order book reflects the current placements of the liquidity providers, based on their information about the value of the asset and the arrival rate of the market orders. The liquidity providers compete with each other for market order-flow that results a characteristic shape for the order book in equilibrium. Dynamics of this structure are closely related to the resiliency of electronic exchanges, which is known as one of the characters of market liquidity. In our terms, market resiliency is the recovery process of the order book in response to temporary market order imbalance, involving the dynamics of price, order-flow and the shape of the limit order book. We explore how the market order flows are influenced by the current states of the limit order book, and vice versa, how market trade modify the configuration of the limit order book.

The evolution of the limit order book is explained in numerous theoretical papers, among others, in the seminal works of Foucault (1999), Parlour (1998), and Rosu (2009). According to them, competition of the liquidity providers forms the features of the market, such as the bid-ask spread and the depth, moreover the shape of the limit order book. These theories explicate how rational market players do limit order placements strategically and how the typical limit order book structures are built up.

Market order flow may influence the limit order book in two ways. While new information may drive to permanent transformation of the limit order book, sudden liquidity needs of uninformed traders can cause temporary effects. There are market trades which do not eat up the entire depth at the best level, but they bring some information about the value of the traded asset. While the price impact of market orders are commonly examined in the literature, market impact for the limit order structure has not been investigated yet in details. When limit orders in the book are eaten up by non-informative aggressive market orders (e.g. one large order or a group of consecutive market orders), limit order structure changes mechanically right after the trade, but it recovers later on to the equilibrium state. The process of limit order book readjustment is not documented empirically well.

Majority of the theoretical expositions supposes that market order flows are exogeneous and evolve independently from the actual state of the limit order book. On the one hand, this is a common and tractable assumption. Impatient traders who submit market orders can be more informed about the value of the asset then the patient traders. On the other hand, imbalances of the limit order book may have some significant effects on the trading strategies of market players. Rosu (2015) highlights that liquidity providers can possess "soft" information (new information that cannot be profitably traded with market orders), which should recoil to the market order flow as well. As a consequence, limit orders can reveal some information, thus market order flow and limit order book should be jointly examined.

The understanding of the process of order book resiliency may serve better information both for liquidity takers and providers. Liquidity takers are able to plan their order splitting strategies better by considering the evolution of the entire immediate price impact function instead of the evolution of the future prices (market impacts of the trade). Liquidity providers can track on the transformations of the limit order book after a market transaction. By following their limit order placements during the transition, they can enhance their limit order monitoring costs. Immediate price impact predictions can be used for regulatory purposes as well, for example, liquidity adjusted value-at-risk models can benefit from invoking immediate price impact prediction of trades.

Our study addresses two main questions about the order book resiliency. The first question regards to the relation between market orders and the cost of trade. In our terms, cost of trade is the difference that a market order submitting trader pays more than the mid-quote, or receives less then the mid-quote. That is a one-sided extension of the bid-ask spread. We are curious to know how this trade cost influences the market order flow. Do large one-sided trade costs imply low demand for liquidity (market buy or market sell)? Do bid and ask trade costs signal the direction of future trades or the future prices? What is the stronger effect, the liquidity demand elasticity or the signalling effect? What sould be the proper way to measure these effects? By extending the examination of one-dimensional trade costs, we consider the market impacts for the structure of the order book in our second question. What happens typically after a market trade with the structure of limit orders? What are the mechanical and the non-mechanical effects of trades for the shape of the limit orders? As limit order monitoring costs decreased in the last decade, liquidity providers prefer to use algorithmic trading for placing their limits in the book. These players can revise their order placement strategy very fast in response to a market trade. Do liquidity providers peg the limit orders to the mid-quote? Does the limit order book take the same shape as it was before? Is there any permanent effect of a trade because of the information content of market orders? What can we learn from the rearrangement process of the book?

Our main academic contributions are the following. To answer our first question, we develop a model to describe the price dynamics taking into account the evolution of the costs of trade. Assuming that bid and ask side costs of trade revert to their means, and trade costs influence future market order flow, we model the ask and bid quote changes, the bid and ask side costs of a trade and signed trade size in a difference equation system. We use stock market transaction data from the Budapest Stock Exchange for the two most liquid Hungarian stocks, the MOL and OTP for the period between September and October in 2013. This high frequency dataset contains the intra-day cost of round trip data, named Budapest Liquidity Measure. Our tests confirm the information signalling role of the bid and ask trade costs and moreover the tests verify the mean-reversion (recovery) hypothesis as well. We find also that market orders have significant direct effects on the trade costs. To explore our second question, we extend our trade cost approach to the immediate price impact function concept. Immediate (or virtual) price impact function depicts the costs of an immediate (a hypothetical, hence virtual) trade over the mid-quote in different trade sizes. We identify three main components which characterizes this function. Over the spread, that measures the distance from mid-qoute to the best quote, we detect slope, convexity and hump-shape are the significant attributes what describe the liquidity structure of the order book. These components are very similar both on the bid and ask sides. We extend our first model with these attributes to get more precise picture about the immediate price impact function movements. According to the impulse-response simulations based on the estimation of the VAR model, we document the direct mechanical effects and the limit order replenishment effects in the transition periods. Our results confirms the hypothesis about pegging of limit orders, we find permanent impacts for the price without any long term effects onto the shape of the immediate price impact movements. In this term, the limit order book recovers to its equilibrium state. For testing robustness of our results, we repeat our examination considering aggressive market orders. These orders divert the best bid or ask quotes. We find stronger direct mechanical effects and the same results in qualitative terms. Moreover, we construct an event study analysis for having a look on the pre- and post-periods of the aggressive orders that also verifies the predictions of our VAR models. Our limit order book resiliency analysis may also serve some practical implications. With the simulated order book components market players can forecast their impact not only for the market price but for the market liquidity as well. The proposed method can be implemented by liquidity takers and providers to add market resiliency into their decisions about trading.

The rest of the paper is structured as the following. Section 2 briefly reviews the literature of market resiliency and clarifies the concepts of price impact, price recovery and order book recovery. We present in details our research design in Section 3. Section 4 investigates our empirical finding and evaluates the results. Section 5 provides the description of the robustness tests. Finally, Section 6 concludes.

2 Market Resiliency and Order Book Dynamics

It is usual to describe market liquidity on order driven exchanges with static dimensions (tightness, depth and breadth, general overviews laid down by BIS (1999) or Lybek and Sarr (2002)) and dynamic ones, such as immediacy (e.g. Harris (1990)) and resiliency (e.g. Kyle (1985)).

Authors, such as Garbade (1982), Kyle (1985), Harris (2003) define market resiliency as how quickly prices revert to former levels after they change in response to large order flow initiated by uninformed traders. According to the seminal paper of Glosten and Milgrom (1985), this price discovery process appears as a consequence of the adverse selection costs. Because traders do not know whether the new order was provided by an informed trader or not, there will be some impact of the trade on the price. In contrast to price discovery, price recovery is assigned by inventory control costs in the market maker literature. However this analogy can be applied in limit order markets, the theory often connects the recovery process to the limit order submitting procedure of the liquidity providers after an aggressive order eats up the limit placements. Hence, theoretical papers, such as Foucault, Kadan and Kandel (2005) and Rosu (2009) define market resiliency as the speed or the probability of that the spread reverts to its former level before the next transaction following a liquidity shock. Rosu (2015) suggests that the market resiliency as the character of the recovery process should be extended not only by the spread and depth but by the structure of the limit order placements.

In empirical studies, price recovery process is often modelled by a vector-autoregressive system that is eligible to measure the information price impacts of trading as well. Among the pioneers, Hasbrouck (1991) uses a vector-autoregressive model to analyze the impact of market orders. This approach focuses on the interconnection between price and order-flow, order book structure is rarely involved into the analysis. Hasbrouck observes negatively autocorrelated returns as a consequence of mean reverting mid-quotes and estimates information price impact to show how a trade permanently shifts price. However, bid and ask side price impacts are not symmetric. Engle and Patton (2004) find evidences for a strong asymmetric impact of a trade on bid and ask prices in the short run. Similarly, Escribano and Pascual (2006) conclude that an unexpected buy order has a bigger effect on average on the ask quote, than an unexpected sell trade on the bid quote, since the buyer initiated trades are more informative. Some authors extend this research direction by taking the speed of the trade into the analysis. According to Easley and O'Hara (1992), the duration between consecutive trades can be a good indicator of the appearing market news. Later, Dufour and Engle (2000) incorporate this duration measure to exploit the new information. They propose that the market is more active when the ratio of informed traders increased in the market. Other authors extend these investigations by market depth. Coppejans, Domowitz and Madhavan (2004) analyze price impact dynamics and its relation to depth and volatility and emphasize the clustering phenomenon of market depth. Using separate ask and bid market depth measures, they find that the volume and market depth is concentrated in certain points in time, thus strategic order placements have economic value. Clustering is also present such as increasing depth on the one side of the book enhances depth on the opposite side as well. Inserting bid-ask spread and volatility into the equation, Hmaied, Grar and Sioud (2006) conduct a similar analysis in an emerging economy, on the Tunisian stock market. They also confirm that depth and price recovery is faster if a security is more intensely traded.

A market trade may cause price overreaction which is usually followed by a price recovery process. When an aggressive order eats up several levels from the book, market depth is insufficient to meet the instantaneous needs, order book will signficantly change. Later on, liquidity provider traders refill the book. Authors often specify price resiliency as recovery events after uninformed trades because it is easier to interprete and measure the recovery without any permanent impacts induced by new information. Degryse, De Jong, van Ravenswaaij and Wuyts (2005) apply event study methods on Paris Bourse data. According to them, market depth stays around its normal state before and after aggressive orders, but spread recovery takes more time. Using a more general definition of resiliency, they find that aggressive orders are informative and cause persistence price impacts. Muranaga (2005) confirms these findings in a similar event study about the Japanese stock market. Price resiliency can be driven by many factors, Dong, Kempf and Yadav (2007) identify the determinants as trade speed, tick size, transaction size, bid-ask spread, adverse selection costs and unexpected volatility. Large (2007) suggests to examine price resiliency by Hawkes self-exciting jump processes.

Order book recovery is in close relationship with the dynamic models of limit order trading and the limit order structure analysis. Foucault (1994), Foucault (1999), Parlour (1998), Goettler, Parlour and Rajan (2005), Rosu (2009) and Large (2009)) contributed to the formal interpretation of these dynamic models focusing on order submission strategies and order-book explanations. Majority of these papers study how limit order book varies as a consequence of a competition among liquidity providers for order-flow. Wuyts (2011) builds a vector-autoregressive model incorporating different dimensions of liquidity to examine the impacts of the aggressive orders on the order book. The observed spread, depth, order book imbalance indicators reverts to a steady-state value within some periods after a shock. Wuyts also presents bid-ask asymmetry: shocks have a more intensive effect on the ask side. The reverse causality is also present, order flow is not independent from the state of the order book. Among others, Biais, Hillion and Spatt (1995), Griffiths, Smith, Turnbull and White (2000) and Ranaldo (2004) find that buy limit order is more likely when the book on the sell side is deep and less likely when the buy side is deep. One approach for interpreting limit order book snapshots is the immediate or virtual price impact function (Bouchaud and Potters (2002), Lillo, Farmer and Mantegna (2003)). Connecting immediate and information (or empirical) price impacts, Weber and Rosenow (2005) find that because of negative correlation between price changes and order flow, information price impact function is generally flatter then immediate price impact function. Applying cost of round trip measures is an other approach for describing the limit order book structure. Using event study method on Xetra data from Deutsche Börse, Gomber and Schweickert (2002), Gomber, Schweickert and Theissen (2011) observe that cost of round trip liquidity indicators quickly reverts to "normal" levels after a large shock. Nigmatullin, Tyurin and Yin (2007) conduct principal component analysis to determine general factors of roundtrip cost curve in case of NYSE stocks. They attempt to identify information shock by generating impluse-responses of the innovation of the established components. In spite of the numerous progressive studies, explaining the cost of trade and predicting slope and hump-shape dynamics of the book driven by a normal order-flow is remained an open question.

3 Research Design

In this section we develop our hypotheses about the role of the limit order book in trading and about the limit order recovery. We also present details about our dataset and the applied methods. In the entire analysis, we use the following terms as synonyms: immediate price impact function, cost of trade curve, configuration of the limit orders, shape of the limit order book. All of these expressions can be derived by the framework of the marginal demand-supply curve (see in Acerbi and Scandolo (2008)).

3.1 Hypothesis Development

To derive our hypotheses, we go back to Rosu (2009) 's theory of the limit order book. In our framework of the limit order book models, there are patient traders (or liquidity providers), and impatient traders (or liquidity takers). Impatient traders conduct market transactions because they have new information (informed traders) or the have liquidity needs or other else reason to do trade (liquidity traders). Patient traders may also have private information about the asset value, however this is more uncertain ("soft") and cannot be traded (for example it is between the available bid and ask quotes). There is a trade-off between exectution risk and winner's course when patient traders place their limit orders. Execution risk means the low possibility of execution if limit quotes are so far from the best quote, winner's course denotes the alternative cost of the realized deal to profit of the trade on the second best quote. Liquidity providers with heterogeneous expectations on the market trade size compete to each other resulting a hump-shaped order book structure. In general, liquidity providers should consider the trade volume submitted by liquidity traders and waiting time (execution risk) and the limits provided by the others (winner's course). Concentrating on the spread, Foucault et al. (2005) emphasize the importance of the arrival speed of the market and limit orders. According to them, spread should be higher when market order arrival rate is higher than the limit order arrival rate. Rosu (2009) explains the spread and the shape of the limit order book by strategic limit placements in a Markov perfect equilibrium game. In his model the immediate price impact function (configuration of limit orders) can be either concave or convex depending on the distribution of the arrival rates of multi-unit impatient traders. However Rosu depicts a tractable frame of the equilibrium and gives implications on the spread reversion as well, he does not serve any predictions about how the order book transforms in response to a market trade and ignore the soft information content of limit orders. Recently, Rosu (2015) deals with the dynamics of the problem in a very formal economic model that is also related to our study. We construct a model to explain the market price evolution by taking into account the cost of trade. The bid and ask side trade costs are determined by the configuration of limit orders. The basic idea of our model is the trade costs caused by immediate price impacts influence the decision of impatient traders about the direction (sell or buy) of their market trade. We adjust Hasbrouck's approach by incorporating price evolution and market order flow with the cost of trade where liquidity providers replenish the limit order book. In this pure limit order exchange approach we do not suppose the presence of market makers. In contrast to Hasbrouck, we do not assume inventory holding behavior of traders, however one can easily develop the inventory holding effects in our proposed model as well.

In our model there is only one market order and several limit orders in one period. Between two market orders a number of limit orders can be placed which reconfigure the order book. Following the notations and the logic of Foucault, Pagano and Roell (2013) on pages 166-175, we model the market price equals to the combination of the μ expected public value of the asset and the sign of the market order flow (d has two states: +1 or -1):

$$p_t = \mu_t + \gamma d_t \tag{1}$$

where γ denotes the order processing cost, for example transaction costs of the liquidity providers ask for the deal. Thus, ask and bid prices can be derived as $a_t = \mu_t + \gamma$ and $b_t = \mu_t - \gamma$. We express asset value as the sum of the former value, the unexpected trade and a noise:

$$\mu_t = \mu_{t-1} + \lambda \left(q_t - E\left[q_t \left| \Omega_{t-1} \right. \right] \right) + \varepsilon_t \tag{2}$$

with λ measure of the information asymmetry that amplifies the surprise effect. In the equation, variable q denotes the signed trade volume. The market players anticipate q based on the former market order flow adjusted by the bid and ask side trade costs:

$$E\left[q_t \left| \Omega_{t-1} \right. \right] = \phi_t q_{t-1} + \sigma^a c^a_{t-1} + \sigma^b c^b_{t-1} \tag{3}$$

where c means the difference of the actual cost of trade to equilibrium level of the trade costs. Both for the ask and the bid sides it can be written as:

$$c_t \equiv C_t - C^*_t \tag{4}$$

where C measures the adverse price movement cost and C^* is the equilibrium level of the trade cost. The mechanism is the following. When ask cost of trade is high, there can be two effects onto the signed size. On the one hand, demand elasticity of liquidity takers suggests that expected trade size decreases, even more, it turns to sell from buy. This phenomenon is documented by Ranaldo (2004), who finds that traders submit more aggressive orders (limit orders between bid and ask or market orders eating up the bid and ask) when the limit order book is deeper on their side. On the other hand, high cost of trade signs for liquidity takers that placements are at higher limit levels in the order book. This can be a new source of ("soft") information for the impatient traders. Hendershott, Jones and Menkveld (2011) emphasize the growing role of algorithmic trade and they argue on that algorithmic liquidity providers decrease the information asymmetry on the markets. Bloomfield, Maureen and Saar (2005) show by laboratory experiments that informed traders sometimes use limit orders. Furthermore, Kaniel and Liu (2006) argue that informed investors prefer to use limit orders under some market conditions. We formulate the evolution of the trade costs as well. Ask and bid side costs of trade have the following dynamics:

$$c_t^a = \theta^a c_{t-1}^a + \pi^a q_{t-1} + \xi_t^a \tag{5}$$

$$c_t^b = \theta^b c_{t-1}^b + \pi^b q_{t-1} + \xi_t^b \tag{6}$$

when θ is an autoregressive coefficient. We suppose that the cost of trade converges to the equilibrium level in time as limit orders arrive or disappear, thus the coefficient should be $0 < \theta < 1$. The limit order book is not entirely independent from the trade in the past. Let denotes π the effect of a market order for limit order replacement. For example, if there is a buy trade, it mechanically increases the cost of trade, because it eats up some limit orders. Later on, new limit orders might arrive responding to the lack of liquidity in the book. We assume that these costs are generally noisy in time, because of some random arrivals of limit order or order cancellations. However, we interprete innovations in these equation as the soft information about future asset value. Combining the parts together, price evolution forms as

$$\Delta p_t = \lambda q_t - \lambda \phi q_{t-1} - \lambda \sigma^a c_{t-1}^a - \lambda \sigma^b c_{t-1}^b + \gamma \Delta d_t + \varepsilon_t \tag{7}$$

that says price changes should not be independent from the present and past order-flows and the former state of the limit order book that reflects the demand and supply of immediate liquidity. To get a better picture, we arrange our model in the following system of equations:

$$\Delta a_t = \lambda q_t - \lambda\phi q_{t-1} - \lambda\sigma^a c^a_{t-1} - \lambda\sigma^b c^b_{t-1} + \varepsilon^a_t \tag{8}$$

$$\Delta b_t = \lambda q_t - \lambda\phi q_{t-1} - \lambda\sigma^a c^a_{t-1} - \lambda\sigma^b c^b_{t-1} + \varepsilon^b_t \tag{9}$$

$$c^a_t = \theta^a c^a_{t-1} + \pi^a q_{t-1} + \xi^a_t \tag{10}$$

$$c^b_t = \theta^b c^b_{t-1} + \pi^b q_{t-1} + \xi^b_t \tag{11}$$

$$q_t = \phi q_{t-1} + \lambda\sigma^a c^a_{t-1} + \lambda\sigma^b c^b_{t-1} + \eta_t \tag{12}$$

where we modified our previous model setup by modelling ask and bid variation separately, supposing that they are not cointegrated. The innovation of signed size is the η order-flow that drives the market in principal. Innovations in trade cost equation may contain soft information. Residuals in bid and ask variation equations do not bring any additional private information, they reflect to the new public information. All residual variables are independent to each other.

H1. *According to our first hypothesis, the bid and ask side trade costs play role in the price evolution.*

- H1.A *Information mechanism is effective:* $\sigma^a > 0$ *and* $\sigma^b < 0$ *(against to demand mechanism where* $\sigma^a < 0$ *and* $\sigma^b > 0$*).*
- H1.B *Trade costs revert to their equilibrium levels:* $0 < \theta^a < 1$, $0 < \theta^b < 1$
- H1.C *Market trades have mechanical effects on trade costs:* $\pi^a \neq 0$ *and* $\pi^b \neq 0$.

While the drafted test seems to be straightforward, this approach has a drawback. It ignores that the trade costs are not equal for all trade volume in a specific time. In other terms, however we can have a picture about important characters of the market, the suggested method does not explain comprehensively the limit order book transformations. We are also curious to know what impacts a market trade implies for the shape of the immediate price impact function. Readjustment of market depth is empirically investigated by Wuyts (2011), but the readjustment of other order book attributes, such as the hump-shape can be also important, because we can reveal more information about the behavior of the liquidity providers even if they are algorithmic traders. The distance between the limit order concentration and the best quote depends on the anticipated execution risk. A market trade can imply diverse movements at different volume levels of the limit order book. It is not obvious whether it modifies the expectations about the execution risk or not. What kind of temporary effects can we find because of a market trade? What attributes of the price impact functions (structure of the limit order book) modifies at that time? What are the typical mechanical movements of the curve? What are the typical movements induced by liquidity providers? It is often observed, that patient traders peg their limit order placements to the actual mid-quote. This means the immediate price impact function recovers to its equillibrium state. This kind of pegging mechanism is not entirely unknown in the literature. It also supports the assumption about the effective monitoring of limit orders, when the patient players are willing to cancel and replace their orders in all of the cases when a new trade comes. Rosu's theory predicts no effect on the change of the price impact function. Only if the arrival rate or submitted volume of the liquidity traders change, or the players anticipate high positive autocorrelation among trades, then the patient traders place more limit on the specific side of the book. Moreover, permanent effects would imply heterogeneity in the evaluation of a market trade among liquidity providers. Can we find any significant permanent effects of a market trade?

H2. *According to our second hypothesis, liquidity providers "peg" their limit orders to the mid-quote.*

H2.A *Market trade has significant temporary impacts onto the shape of immediate price impact function.*

H2.B *Market trade has no permanent effects onto the shape of roundtrip cost curve, it only widens the spread.*

In the latter part of the study, we set up and estimate an empirical model to explore these hypotheses.

3.2 Data

The study uses stock market intraday data provided by the Budapest Stock Exchange. However, only two of the most liquid stocks are analyzed here, the dataset contains wide range of information about the transactions and the cost of round trips. The total observations cover a two-months period from 02/09/2013 to 31/10/2013, this means altogether 43 trading days. An event is recorded when a market order, limit order submission or cancellation have occured. The data is aggregated up to one second. The quality of the dataset is close to event-by-event data, because the intra-second events are relatively rare on the observed market. The entire dataset consists of time stamps, mid-price, bid and ask levels, spread, total number of price levels in the book (bid and ask side separately), total volume of bid and ask limit orders in the book, the market transaction price and volume, and the cost of round trip indicators. The Budapest Stock Exchange recorded the so-called Budapest Liquidity Measure cost of round trip indicator, which originates from the Exchange (alias Xetra) Liquidity Measure developed by Deutsche Börse (Gomber and Schweickert (2002)). The common definition of the roundtrip cost is "*the weighted average price at which an order of given size could be executed immediately* *at time t*" (Gomber et al. (2011)), that is calculated in the percentage of the mid-price at the Budapest Stock Exchange. The added value of the dataset is that it provides cost of round trip indicators at eleven levels, and one-sided cost of trade indicators at eleven bid-side and eleven ask-side levels for each second over the conventional market transactional data structure.

The two most liquid Hungarian stocks are OTP, the leading commercial bank and MOL which is the biggest company from the oil industry in the country. The market capitalizations of these firms are 4.4 billion EUR for OTP, and 4.6 billion EUR for MOL, the free floats are approximately 64 percentage and 44 percentage. These two stocks are the most frequently traded stocks on the Budapest Stock Exchange, with an average daily traded volume of 3.3 million EUR for the MOL, and 16.5 million EUR for the OTP in 2013.

During the examined time period, Budapest Stock Exchange operated MMTS trading system. (The Exchange has installed and now operates Xetra trading system in the stock trading section since December 2013.) The trading rules at that time in the Exchange was very similar than in the European order-driven stock markets. There were three sessions in a trading day: pre-trading, trading and post-trading sessions. Market transactions were only executed in the trading session. Trading session started at 9 a.m. and ended at 5 p.m., there was a two minutes warm-up before active trading from 9 a.m. to 9.02 a.m. Traders were able to submit two main types of orders: market orders and limit orders. Trades were able to cancel the formerly placed limit orders before execution. The immediate market impact was bounded by a regulatory constraint. That is, market orders were executed only on the first quote level, namely only on the best bid or on the best ask. When the volume of market order exceeded the available volume at the best quote, the rest of the order was deleted.

The traders could choose the availability of a limit order by submission. There was an option to cancel limit orders at the end of the trading day automatically. Altogether the 20 bid and 20 ask best levels of the book were public for the traders. Typical number of these levels for the major stocks were counted from 150 to 800. The tick size was fixed, for MOL, one unit was 5 Hungarian Forints, (the domestic currency unit) that was approximately EUR 5/300, or 1.67 eurocents. For OTP, it was one Hungarian Forint (EUR 1/300), that is around 0.33 eurocents. The tick size was small compared to the transaction price. MOL share price varied around HUF 15,000 (EUR 50); OTP varied around HUF 5,000 (EUR 16.6). Counterparties of the market transactions were publicly reported immediately after the trade. In contrast to New York Stock Exchange, there has not been any specialist on the market, the Exchange was a pure order-driven market.

We start the analysis with introducing some general statistics of trading. Table 1 shows summary statistics about the number of orders on daily basis in the observed period. On an average day around 720 OTP and 385 MOL market transactions were executed. Limit order submissions are three times more frequent than market orders and twice more than order cancellations. According to the median number of orders, the market order - limit order ratio is around 1:3 and the cancellation over limit orders ratio is around 1:2 in both of the cases, that signs algorithmic trading activity among the limit order submitters.

[Insert Table 1 here]

The value of the transactions are around 1.3-1.5 times larger than the limit orders. Value of limit cancellations are close to the value of submitted limit orders. Average value of the market order is around EUR 13,000 in case of OTP and EUR 10,000 in case of MOL. Medians are lower, around EUR 5,500 and EUR 4,500.

The dynamics are not independent from the speed of orders. It is well known that speed of order submissions is different in different time on a trading day. To evaluate the main characteristics of the speed of market and limit order submissions, and limit cancellations, we calculate the sample average for the durations of order submissions. Time elapsed between the same type of orders are counted in seconds. Furthermore, for describing intraday seasonality, we also calculate these durations for 16 half-hour periods that covers trading day.

[Insert Table 2 here]

The speed of the orders are the highest right after opening and before closing. Regarding the overall day evaluation, we document both mean and median values of the time elapsed between consecutive orders in seconds. Typically, the ratios on mean elapsed time of market-limit orders and limit-cancellations are 1 to 1.5 and 1 to 3. In median terms, limit order submissions are twice faster than market orders and cancellations, which are held almost the same time. Median values are lower than means that signs asymmetric distribution of arrival times, close to exponential distribution.

3.3 Methodology

There are two common approaches to capture the structure of the limit order book. One is using limit order levels as is and the other is using round trip costs. This indicator shows the round trip execution cost of a market order which is defined by the v targeted value of the trade. Among the empirical studies, Gomber and Schweickert (2002) and Gomber et al. (2011) introduced the cost of round trip indicators into the discussion by investigating Xetra data from the German stock market. Similarly to the Deutsche Börse's Exchange Liquidity Measure (XLM), Budapest Stock Exchange also reports Budapest Liquidity Measure (BLM). These measures are the sum of two components, the so called liquidity premium and adverse price movement. We define liquidity premium as the relative half-spread in basis points, or

$$LP \equiv \frac{a-b}{2m} \times 10\ 000 \tag{13}$$

where a and b denotes the best ask and bid quotes in the book, and m means mid-price. This measure serves as a proxy of market tightness. Adverse price movement can be expressed as

$$APM^a(v) \equiv \frac{A(v) - a}{m} \times 10\ 000 \tag{14}$$

for the ask side, and

$$APM^b(v) \equiv -\frac{B(v) - b}{m} \times 10\ 000 \tag{15}$$

for the bid side, where $A(v)$ and $B(v)$ is the average price on what a hypothetical trade (buy or sell) can be executed with v euro amount at a certain time. APM can be used as the proxy of market depth at different transactional volume levels. Budapest Liquidity Measure is calculated as $BLM(v) \equiv 2LP + APM^b(v) + APM^a(v)$, it can be interpreted as a weighted spread measure for different order sizes (Kutas and Végh (2005)). Our dataset contains these liquidity premium and adverse price movement measures for the ask and bid sides of the limit order book. The exchange recorded these liquidity indicators for eleven different order sizes, for those seconds of trading, when there was any kind of change in the order book. This means that snapshots are documented for all transactions, limit submissions and limit order cancellations.

We show some statistics about liquidity premium and adverse price movements of seven levels in Table 3. We find that adverse price movement measures at the very large volume levels do not change in the observed period, thus we skip levels 8-11 from our further analysis. We use altogether seven levels for bid and seven levels for ask side of the book. All of the indicators are percentage of the mid-price. The liquidity premium equals to the half spread over mid-price, adverse price movement measures are calculated as the cost of trading on a certain amount over mid-price minus the liquidity premium.

[Insert Table 3 here]

The mean and the standard deviation of the costs increase as the volume increases. The table also details the distributions of each adverse price movement measure.

[Insert Figure 1 here]

The means of the adverse price movement indicators draw the "APM-curve" which is slightly concave in the function of volume. Figure 1 depicts the average shape of the limit order book where we plot the total round trip costs in basis point value: $(A - m)/m$, where A denotes the average ask price at a certain amount of buying and m is mid-quote, $-(B - m)/m$ and B brings the similar meaning. However the average curve is concave, we could observe linear and convex forms in certain periods as well.

We develop a vector-autoregressive (VAR) system to describe market resiliency as the recovery of limit order book structure to normal features. We extend Hasbrouck (1991)'s mid-price and order sign bivariate VAR approach with variables that may effectively describe the limit order book structure. Moreover, contrary to that well-known model we use the returns of bid and ask levels rather than mid-quote returns. Our model carries also some similarities with the model presented by Wuyts (2011). In contrast to Wuyts we do not investigate on the aggressive orders and trade size effects, but we use the components of bid and ask side adverse price movement dynamics to describe the recovery process of the order book, instead of other market depth proxies. The general formula of our vector autoregressive model follows

$$y_t = \sum_{l=1}^{L} Ay_{t-1} + \sum_{m=0}^{M} Bx_{t-m} + Gz_{t-1} + e_t \tag{16}$$

where y vector denotes endogenous and x and z vectors mark exogenous variables. Notation for the number of lags are L, and M. The equation is represented in transaction time, that means time refers to the moments of market trades. The model possesses eight endogeneous variables. The vector of endogenous variables consists of the differences of logarithmic ask and bid quotes, the limit order book (or cost of trade) components and the sign of the market order:

$$y_t \equiv \{dlogask_t, dlogbid_t, COT.Comp_t, q_t\} \tag{17}$$

We specify $COT.Comps$ in the latter part that explicates the results. The sequence of the endogeneous variables is selected based upon some theoretical assumptions. Order flow equation is the last in the sequence because order-flow brings the major part of the innovations. Both $dlogask$ and $dlogbid$ variables are publicly known for all players and have instantaneous impact on the other components, therefore we select to keep them in the first places in the order of equations. There is no particular reason why ask-side variables overtake bid-side statistics. We model buy trade shocks that adjust ask side in principal, this suggests the specified order. We presume that our choice does not modify significantly the outcomes. Many of former studies, such as Wuyts (2011) and Engle and Patton (2004) find that ask and bid quotes are cointegrated, that is found in our case as well. We do not impose other cointegrating relations since only bid and ask quotes are found to be first order integrated. Book components, as the other endogeneous variables are zero order integrated. This implies that the VAR-model must be specified in error correction form. We estimate $dlogask$ and $dlogbid$ variables in the model and put into the equation the lagged difference between logAsk and logBid as an exogenous variable denoted by z, such as:

$$z_{t-1} \equiv logSpread_{t-1} \tag{18}$$

where $logSpread$ represents the cointegrating term. Intraday trade analysis requires to filter out the diurnal effects of trading fluctuations. For this, we splitted the trading day into 16 half hour sections and created time dummies for each one. To avoid perfect multicollinearity, we use only 15 dummies by omitting the last. Some characters of intraday seasonality carried out by Table 3 that was evaluated before. A dynamic approach of market structure must deal with the speed of the order submissions. Both of theoretical and empirical works argue on that time elapsed between consecutive orders should be taken into account during modelling. While applying durations of the market order is more common in these kind of analyses, one cannot avoid using limit order durations when predicts the dynamics of the limit order placement structure. We calculate the time elapsed between two market orders and between two limit orders for the moments of all transactions. These durations are measured in seconds, some statistical properties were introduced by Table 3. We use the logarithms of durations in the regressions to control on the speed of the market. In sum, the vector form of the exogenous variables are

$$x_t \equiv \{T_{01}, T_{02}, \ldots, T_{15}, logDur.MO_t, logDur.LO_t\} \tag{19}$$

where T denotes time dummy, MO and LO stand for market and limit order.

4 Empirical Analysis

The structure of this section is the following. At first, we analyze the hypothesis of the relationship between market order flow and trade costs. For next, we turn to the second hypothesis. We expose the results about the determining components of the order book structure. Using the components we conduct the VAR-system estimations and analyze the generated impulse response functions.

4.1 Trade costs and market order flow

To measure the interconnectedness of market order flow and trade costs, we extend our theoretical equation system to a complete vector-autoregressive model. We use all variables for explanatory variables and we use more lags to reveal the effects over one period. Proposed by Schwarz information criterion, we find that optimal lag number is $L = 4$ for OTP and $L = 3$ for MOL tickers. Among other criteria (e.g. Akaike, Hannan-Quinn or final prediction error) Schwartz criterion suggests the lowest lag. We remark here that it is common to choose $L = 5$ lags in the literature, but larger lag number does not significantly add more sense to explain short term dynamics for this examination. We select the number of lags for exogenous variables $M = 0$. All of the variables have no unit root according to Augmented Dickey Fuller-tests. We specify cost of trade as the immediate price impact of an unusal large trade. This measure consists of the "depth weighted levels" of the order book on the domain where trading is relevant. More precisely, ask and bid costs of trade are calculated as the liquidity premium and the adverse price movement at 70,000 euro level:

$$C_t \equiv LP_t + APM_t\,(70\ 000) \tag{20}$$

We estimate our VAR model with ordinary least squares method. To handle autocorrelation of the residuals and heteroscedasticity issues, we calculate Newey-West t-values for variable significance tests.

[Insert Table 4 here]

As it is shown in Table 4., all of the first lag explanatory variables of *dlogask* and *dlogbid*, moreover the signed trade volume are significant. Considering cost of trade for ask and bid sides, only the first lags of cost of trade variables and signed trade volume are significant, price variables do not or weakly play a role.

However, this is not entirely the same model that we laid down in the theoretical section, it is very close to that and it is reasonable to interpret some of the estimated coefficients. We only investigate here the results for ticker OTP. Having a look at the information role of the limit order book imbalances for market order flow, we find that σ^a is around 0.08 and σ^b is around -0.05 in signed trade volume equation, both of the coefficients are significant. This confirms the hypothesis about effective information mechanism. The (first lag) autocorrelation coefficient of signed trade volume is around $\phi = 0.2$, that is close to Hasbrouck (1991)'s estimation that was 0.167 on his NYSE sample. The order book 'mean reversion' coefficients are also significant and around $\theta^a = 0.7$ and $\theta^b = 0.7$, that supports the idea about a strong recovery mechanism. The effects of the market order-flows on cost of trade are around $\pi^a = -0.02$ and $\pi^b = 0.01$, both are significant at least at 10 % level. It implies that a market buy reduces the ask side trade costs in the next period and increases the bid side costs. At the first glance, the signs of the coefficients seem to be counter-intuitive. However, mid-price and ask price also shift up in the majority of the cases reducing the cost of the trade. Furthermore, the relative structure of the limit order book changes also. It means, in many times when a market buy executes limit orders at the best quote, offered limit order volume at the new best quote will be deeper. This may decrease the adverse price movement effect form the mid-quote, hence the ask side cost of trade lowers. Because of the tick size is relatively small, in the majority of the case, the second effect is much stronger. We also find some evidences about the speed of the orders. Durations in the cost of trade equations are negative, slowdown of arrival rate of market orders decreases the trade cost, so fills the book. The reverse can be observe in the case of limit order durations that suppose that arrival rates influence the round-trip costs. However, we cannot interpret the price equation in the VAR system as in our theoretical model, we can measure the information price impact by impulse response analysis. We get that one standard deviation change in signed trade size causes approximately $\lambda = 0.08$ standard deviation change in the level of bid and ask quotes. Considering ticker MOL, we do not find any particular differences for our qualitative implications. In sum, we do not reject our first hypothesis about the reflexive role between trade costs and market order flow.

4.2 Decomposition of the limit placement structure

Now, we turn to extend the simple trade cost conception to a trade cost structure. For identifying the dominant driving factors of the book structure, we apply principal component analysis on adverse price movement data. Because our vector autoregressive system captures the bid and ask quotes separatelly, we do not add spread-type variables to the principal component analysis. Thus, we consider trade costs beyond the spread and skip the liquidity premium (LP or relative half spread) indicator. Furthermore, instead of using the levels of adverse price movements, we construct cross-sectional differences of the APM indicators to avoid overlaps. These differences are calculated as

$$APM\left(v_{i,t}\right) - APM\left(v_{i-1,t}\right) \tag{21}$$

where v_i means the certain volume on level i at time t. Altogether we have six differences and we complete this with the first level adverse price movement that can be considered as also a difference between the first level and the best quote. This results seven measures. Employing the principal component analysis method, we transfrom orthogonally the seven variables using correlation matrix for the computations and select the three that bring the most of the information. Since the variables are in basis point forms, we suppose that these scaled variables can be considered as a normalized variable also, hence we take into account the variability differences among these variables. PCA is computed based upon the correlation matrix.

Table 5 shows the loading of the three components, setting apart the bid and ask side of the book. We show details for both of the securities. The first three components together explains around the 75 percentage of the "marginal APM-curve".

[Insert Table 5 here]

To get more interpretable results, we have multiplied by minus one all of the first and second components, except the second component of bid at the OTP ticker. Hence, the loadings imply that the three most important components are the level, the slope, and the curvature of the marginal APM-curve. After translating these components to the "natural" APM-curve, we can indentify three attributes of the structure: *slope*, *convexity* (curvature or quadratic part) and *hump-shape* (cubic function like shape). The graphical representations of the components are obvious, the second component suggests a measure for convexity of price impact functions, the third signs the temporary concentrations of the limit orders. There is a high similarity between bid and ask side components. Although, this similarity does not infer automatically similar dynamic behaviors of the curves, but it verifies the commonalities of the structure in general. However, the two securities differ in trade size and liquidity, we could not find significant differences between the tickers on the resulted loadings. This may suggest that typical variations of the order book structure are not heavily influenced by trade size and number of orders. Figure 2 visualizes the PCA loadings of the first three components that have the highest explanatory power.

[Insert Figure 2 here]

These results are in close relationship with Nigmatullin et al. (2007)'s work. Contrary to them, we run principal component analysis setting apart the bid and the ask side, and we model comovements of the two sides with the VAR approach in the latter part of this study. The referred authors explored four factors of the APM-curve: two-side shift, opposite-side shift, twists in the same direction, twists in the opposite directions. We also find evidences about shift and twist movements, but we argue moreover on the convexity (curvature) and hump (cubic) shape, which are also important drivers of the order book movements. In comparison with their findings, because of the different examination method, we find more factors that describe the one-side limit order structure and we connect the two sides of the book in another way.

The outputs of the principal component analysis give the possibility for approaching the typical shape of immediate price impact curve in a more formal way. Based on the results, we can define the ask and bid side trade costs (or liquidity premium plus adverse price movement) as:

$$c(v) = \beta_0 + \beta_1 v + \beta_2 v^2 + \beta_3 (v - \overline{v})^3 \tag{22}$$

where $v = mq$ and $\overline{v}$ is a threshold for separating the curve into two domains. In our analysis reported in this section, we approximated the coefficients by PCA from the derivative of $c(v)$, that bring similar result as the coefficient estimation of the $c'(v)$ function which looks like

$$c'(v) = \beta_1 + 2\beta_2 v + 3\beta_3 (v - \overline{v})^2 \tag{23}$$

We argue on that one should deal with the linear, quadratic and cubic part of this marginal cost of trade curves even if literature does not emphasize very much the importance of the third part.

The economic interpretation of the components is also interesting. Looking at the formerly introduced expression $(A - a)/m$, a positive increment of this measure can either sign the fall of the mid-quote, or the raise of the $A - a$. It is difficult to identify that ΔA, Δa, or Δm caused the observed variation. To separate these effects we express the ratio after shock as

$$\begin{aligned} &\frac{A + \Delta A - a - \Delta a}{m + \Delta m} - \frac{A - a}{m} = \\ &= \frac{\Delta A - \Delta a}{m} - \frac{\Delta m / m}{1 + \Delta m / m} \frac{\Delta A - \Delta a}{m} - \frac{\Delta m / m}{1 + \Delta m / m} \frac{A - a}{m} \end{aligned} \tag{24}$$

The final formula has three parts: the increments of ΔA and Δa without mid-price change, and the mid-price variation effects interacted with $\Delta A - \Delta a$ and $A - a$. If the latter components are effectively small, we can approximate the variation of the ratio as the change of price differences or ΔA -Δa. This approach gives biased results in this case as well, but we can estimate the size of the bias on the sample. In case of the observed stocks, mid-prices are high compared to the observed tick-by-tick price jumps. We find that the bias is not so large, the range of the midprice change in the sample is $|(\Delta m/m) / (1 + \Delta m/m)| < 0.02$ for both of the securities. Furthermore, we find that $(A - a)/m < 0.013$ and the last part of the equation is dominantly lower than the first one in our observed samples. The low variability allows us to ignore mid-price movements from the dominant driving factors of APM movements during the qualitative interpretation.

To conclude, in our case where tick size is relatively small, one can interpret APM movements as limit order structure changes. Decreasing slope of the curve indicates new limit orders in the book, curvature captures the hump-shape (limit orders appear far away the best quote), the cubic form reflects to the interim states of the book when limit orders are removed and replaced to somewhere else in the book.

4.3 Immediate price impact function and market orders

This part starts with the specification of the VAR model for the dynamics of the order book. As before, we use the Schwartz criterion for selecting the appropriate lag number. According to this criterion, we set lag number to $L = 3$ in our VAR-systems. The exogeneous variable lag is selected to $M = 0$, we use the concurrent variables. The selected variables do not have unit root according to Augmented Dickey Fuller-tests. Neither an intercept nor a trend were included in the test regressions where number of lags was one. In both of the specified cases, we find that the residuals are autocorrelated. Multivariate ARCH-LM tests detect heteroscedasticity as well. To handle the problem of autocorrelated and heretoscedastic residuals, we calculate Newey-West adjusted t-values for providing the accurate significance level for the estimated coefficients.

In the specifications, the $a1$, $a2$, $a3$ and $b1$, $b2$, $b3$ variables are z-scores of the constructed book components are in basis point values. Negative and poisitve values denote divergences from the most characteristic state. Thus, the equation system describes how the immediate price impact function looks like at a certain time. This approach is able to illustrate what the market participants observe when they follow the evolution of the immediate price impact functions.

Table 6 reports the estimated coefficients. Panel A and B belong to tickers OTP and MOL. We investigate the outcomes commonly for both of the securities. For providing more interpretable numbers, *dlogask* and *dlogbid* variables are multiplied by $1,000$. Variables $a1$ and $b1$ mean the slope, $a2$ and $b2$ the convexity of the immediate price impact functions, and $a3$ and $b3$ represent the cubic shape.

[Insert Table 6 here]

As table 6 shows, the limit order components are generally not heavily influenced by the price changes. Only the slope components are driven by the market order flow (possibly from the price change). All of the components revert to their means, in terms of majority of their own lag variables are significant and between zero and one. Furthermore, all of the components can be explained by the three attributes, however ask side is influenced significantly by ask side variables, and the same holds for the bid side. We find that the price and all components variables significantly explain the q signed size, except the cubic (hump)-shape variables. The q signed size has positive lags that instances to the autocorrelation of market order flow, similarly to the former case. Moreover, the q signed trade size affects *dlogask*, *dlogbid* variables, the directions of the coefficients meet with the intuitions, price increase in case of buying and decrease in case of selling. There are evidences about the price reversion as well. The *dlogask* and *dlogbid* possess significant negative lag coefficients. We find strong correlations among the best bid and ask changes and the structural components of the book as well. The best quotes are not entirely independent from the configure of the limit order book. It is also not surprising, that bid and ask variations weakly comove with the spread variations. Reflecting to the intraday trading patterns, majority of the time dummy coefficients are significant in the *dlogask*, *dlogbid* and order flow equations. Estimated coefficients of logarithmic market order duration variables suggest that slow arrival rate of market orders induce lower ask and higher bid, that is, narrower spread. In case of the order book components, market order arrivals do not explain their distance to their most characteristic state. The higher speed of limit orders have strong negative effects for the ask and bid slope: higher arrival rate of limit orders flattens the trade cost curve. Higher spread significantly increases the slope of the ask and the bid side curves, but it has no significant effects on the other attributes.

The results are robusts in term of the variable specification. Changing the order of the ask and bid variables to bid and ask sequence, we estimate very similar the coefficients and significance leves. Extending the models into $L = 5$ lag VAR systems, the results remain very close to the analysis exposed before.

4.4 Impulse-response dynamics

We generate impluse-response functions to detect the short run and long run effects of the order-flow shocks.

We plot the cumulative orthogonal impulse responses of the logreturns on the best ask and best bid quotes and non-cumulated levels of the order book components. The shock is one-sigma variation of q in the positive direction, that is a buy trade. According to Figure 3, bid and ask quotes shift up after the buy signal, the bid quote shows slightly smaller deviation for both of the securites. This implies the spread may increase on average after a shock and informative buy trade causes a new bid limit submission above the best bid.

[Insert Figure 3 here]

We can also observe the recovery of the limit order structure after an order-flow shock. All of the components significantly divert from zero and recover later on the simulated period. Price impact slopes, the first bid and ask components show the most characteristic movements. The intuition behind the response functions is while the best ask raises, the ask immediate price impact function became less sharp right after the trade. On the opposite side, sharpness of the bid side immediate price impact increases that may mean arriving new bid orders. The curvature of bid and ask price impacts varies in different ways. Let us have a look at ticker OTP, where during the recovery period, immediate price impact is rather convex. In the short term, ask immediate price impact turns to be concave, then it reverts to be more hump-shaped, as new limit orders fill the book. Bid price impact became more convex after a buy trade as well, which can be also the consequence of appearing new bid orders above the best bid. Ticker MOL is an example of the recovery when immediate price impact turns temporarily to be more concave. However the ask curve become more concave temporarily, we cannot detect unambiguous variation for the bid curve. The hump or cubic shape components have the smallest deviations in the simulations. This can be interpreted as a price impact form that contains a hump close to the best quote and a "valley" farther from that. The results are similar for both of the securities. Ask side response of the shock is slightly negative that strengthen the curvature component and indicates more intense hump farther from the best ask quote. The bid curve shows positive response, that means more concentration of the limit orders close to the best bid after a market buy order. In sum, all of the components converge to their equilibrium state in both of the observed cases, we did not find any permanent effects expect the price effects of the trades. We do not find any evidences that rejects the pegging hypothesis. Similar to Wuyts (2011) we found that the specific properties of the limit order book turns back to the original state, but price changes permanently. However we did it for other attributes of the book. We also could confirm that ask side effects are stronger compared to bid side ones.

4.5 Interpretation of the results

Here we propose possible interpretations of the results. At first, we show an application to get more impressions about predictions of the immediate price impact curve changes. Secondly, we give a simple numerical example based on the findings. Finally, we formulate our main conclusions.

To provide a more illustrative way of the movements reported before, we plot the evolution of immediate price impact functions in six steps. We depict the typical ask-side and bid-side curves 1, 2, 3, 5, 10 and 20 periods after a market buy. To emphasize the dynamical effects, we distort the movements in the pictures for drawing a "caricature" of the events after a market buy. The initial curves are kept in the original state, but curves in latter periods are streched. Hence, the figures can only be considered as illustrations.

[Insert Figure 4 here]

Figure 4 shows two kind of snapshot of the immediate price impact curves for both of the observed stocks. The upper figures show immediate price impact curves that an observer can realize after a trade. The lower figures draw the long term price impact curves, that informs us about how much would be the trade cost later on related to the original state at the moment of a buy trade. As the immediate price impact curves turn back into their original forms, there is no recovery in terms of the long term effects of price impacts. There is no readjustment in the sense of the limit order book does not turn back to the initial state.

The impluse-response analysis relates to the transition between two equilibrium states. It shows if there is a market trade, how the order book turns from one equilibrium to the other. However, depth is a good proxy for market liquidity, the second and other level of the quotes proved to be also interesting. Many trades can be only executed on the second best quote, and levels far away the mid-price are able to reflect the anticipations about the market order flow. Now, we can describe how the slope, the convexity and the (cubic) hump-shape of the book change after a trade, and what happens on the opposite side of the book at the same time. We can measure and model the typical way of the readjustment of the limit order book.

Based upon our experience from the results, we construct a stylized example of the order book resiliency. Although it is a very simplified issue, we believe it supports the efficient discussion of the mechanical and non-mechanical movements after a trade. Let us suppose that there are different size of limit orders at ask levels 100, 102, 104, 106, 108 euros. To keep the example simple and avoid the problem of discontinuity, we set the tick size to small in comparison to the price of the asset. Let us suppose that the limit orders are settled down in an equilibrium state. Step 1: A market buy order executes limit orders at 100 euro price level. The immediate price impact function transforms mechanically. Right after the market trades, liquidity providers start to adjust their limits on both bid and ask sides. We detail here a possible reaction in two steps. Step 2: A new bid order established that is better than the best bid. It also modifies the mid-quote. Step 3: Limit orders are replaced on the ask side of the book to move the orders into a new equilibrium state that gives the same cost of roundtrip structure that in the original state.

[Insert Table 7 and Figure 5 here]

The immediate price impact function moves in a very typical way as order book changes. The function close to the best quote sharply increases, the curve become more flat. As the mid-quote increases, the function shifts down. As the order book trasforms into the new equilibrium, the immediate price impact curve reshapes to the original form. To conclude, the process of recovery consists of three steps. By the direct effect of a market buy, the ask side cost of roundtrip curve shifts up and flattens, the bid side curve steepens. By the indirect effect of bid change, the ask side cost of roundtrip curve shifts down. At third, concentration of ask limit orders are replaced to farther from the best quote.

In sum, we provided some empirical evidences about the dynamics of the immediate and the long term price impacts. Typically, a normal buy transaction induces the following process of recovery:

1. The best ask and the bid shifts up mechanically, ask variation is generally stronger.

2. Short term reactions of the limit order book structure:

    - Ask immediate price impact flattens, bid-side immediate price impact become steeper.
    - Ask immediate price impact function transforms to more convex, bid side turns into less convex.

3. Long term responses:

    - Ask curve reverts back to the original slope, it becomes less convex and converges to its steady-state convexity.
    - Bid curve reverts back to the original slope, it becomes less convex and converges to its steady-state convexity.

Altogether, the mid-quote permanently increases and the immediate price impact function depicts typical recovery dynamics and turns back into the original state a predictable way. Our tests verify that on average, the liquidity providers react in very similar way to the market order-flow. The anticipations of the liquidity provider limit order submitters about the execution risk and winner's course modify because of the public information about the value of the asset changes. They peg their limit orders to the mid-quote (dominantly by algorithms).

5 Robustness tests

To validate our findings, we rerun the regressions with an alternative shock identification. We use aggressive market orders instead of normal market trades to check the recovery processes. Although there are many definitions of aggressive market orders, we choose a simple approach that fits for our database where a market order cannot be executed on multiple quote levels. Thus, we define aggressive market order as the market order that eats up one level of the book. In practice, it means that a market order is executed on the best ask or bid level, and abolishes all order at the best level. When the targeted trade size is larger than the available volume on the best quote, it is reduced. We do not investigate the aggressive limit orders in the robustness analysis.

We identified altogether $5,092$ aggressive buys and $5,133$ sells for ticker OTP (total number of observations: $30,789$), and $2,784$ aggressive buys and $3,095$ sells for ticker MOL ($N = 16,533$). The ratio of the aggressive market orders to the total number of market orders in the observed periods 16.5% for buys and 16.6% for sells (OTP) and 16.8% for buy orders and 18.7% for sells (MOL). We report the impulse-response functions in Figure 6.

[Insert Figure 6 here]

As one can see, the movements of the components are even stronger in case of bid and ask convexity and hump-shape attributes. For ticker OTP, the results are almost the same. Experiences about ticker MOL reveal some slight differences. At first, the ask slope variation is not enterily obvious. We remark that tick size is larger in this case and the readjustment of slope depends on it. The conclusions for convexity variations are more clear here than in the original case and brings the same results. The variation of the cubic components seems to be similar, however these changes are not very significant. Summing it up, we do not find any remarkable differences between the aggressive order specifications and the original cases.

For further exploration, we conduct event study analyses of the aggressive orders as well. We create time windows that cover 20 periods before and 20 periods after each aggressive order and calculate the mean of the observations. We execute this procedure for both of the aggressive buy and sell market orders.

[Insert Figure 7 here]

For ticker OTP, we produce these time windows for 15 variables. The figures seem to be quite straightforward. Considering the average effects of the aggressive buy, we can formulate the following statements. For ask and bid quotes, we normalized to the levels to the ask or bid price at the moment of the declared aggressive trade event. Ask and bid quotes jumps at the moment of aggressive buy trade. Price effects are larger on the ask side, bid shows slower convergence to the long term final price. Both ask and bid quotes start to increase before the aggressive trade. It may come from the fact that many of aggressive trade arrive in sequences. Considering signed trade size and trade sign variables, they indicate higher autocorrelations (higher chance to trade in the specific direction) before and after the aggressive buy. Spread variable is normalized to the spread size at the time of the aggressive buy. Interestingly spread is the smallest just before the aggressive buy comes. It is general, that many of new bid limit orders are submitted above the best bid before aggressive market buy arrives. Later on, spread turns back to its original state. Looking on the order book components, one can discover similar movements as impulse-response analysis implies. The variables are normalized to their state at time of the aggressive buy trade. Ask slope ($a1$) immediately drops, then converges to the equilibrium level. Bid slope ($b1$) increases, then reduces to the normal level. Ask convexity ($a2$) fluctuates and goes down before the aggressive event, lifts up by the trade and decreases on the normal level later on. Bid convexity ($b2$) emerges after the trade till it reaches its normal level. However average movements of ask and bid cubic shapes ($a3$, $b3$) are still very noisy, they converge back after the event. Time windows of order placement speeds also serve us some valuable information. Durations between limit orders are very low just after the aggressive buy, liquidity providers fills up the book quickly. Order cancellations also accelarate, this phenomenon indicates active rearrangement of the limit order book through dominantly algorithmic trading. Market orders speed up after the aggressive orders as well, this can be the consequence of that quick consecutive buy orders may follow the aggressive buy. We find very similar picture for the aggressive sell trades. These event studies help to understand the actions in periods prior to the aggressive (or even the normal) trade events as well. We have to remark that the autocorrelation among normal trades is tendenciously lower than the autocorrelation between aggressive market orders. Because of this, the window analysis can depict some charactestic movements before an aggressive trade, that is not necessarily true for a normal trade. Furthermore, we find that normal trades have higher price impacts related to the aggressive trades, that suggests they bring more information for the market players. One can settle similar consequences in the case of ticker MOL, with slight differences in the cases of curvature and cubic-shape attributes.

6 Summary

This paper describes the resiliency of the limit order book structure on pure limit order markets. Our general concept of market resiliency includes not only the recovery of depth and price, but the reconfiguration of the limit order book. We build up a simple limit order model for analyzing the connection between trade costs and market order flow. Using intraday data of two stocks from Budapest Stock Exchange, we find that the causality is for both directions, trade costs may serve some information for the liquidity takers, hence costs of trade influence market order flow. We extend this analysis with focusing on the behavior of the trade cost curves (or immediate price impact functions) to learn more about the limit order book recovery process and examine the relationship between market orders and the current configuration of the limit order book. We detect three major attributes of immediate price impact function beyond the level of the curve that comes from the spread. The three components are slope, convexity, and a special cubic shape that signs humps near to the best quote. Using these components, we rerun the proposed regressions and report the typical movements of the trade cost curves. We find explicable movements that are caused by direct mechanical effects of the specified market trade, and the limit order replenishment process. Immediate price impact variations are different on the ask and bid sides after a trade. Based on the result we suggest a simple procedure for making forecasts about immediate price impact function variations. Applying aggressive orders as shocks, robustness tests are confirmed the predictions of our dynamic model.

We test two main hypotheses about the relationship between market order flow and immediate price impact function. Our examination supports that liquidity providers use (mostly soft) information about future value of the assets and we find that we can explain some of the market order flow in the short future considering the bid and ask side costs of trades. Many of liquidity providers use algortihms for limit order submission and cancellation. We find that these traders peg their limit orders to the mid-quote and the competition among liquidity providers do not change by market orders. After temporary adjustments, the immediate price impact recovers to its original form.

References

Acerbi, C. and Scandolo, G. (2008): Liquidity risk theory and coherent measures of risk. *Quantitative Finance* **8**(7), 681–692.

Biais, B., Hillion, P. and Spatt, C. (1995): An Empirical Analysis of the Limit Order Book and the Order Flow in the Paris Bourse. *Journal of Finance* **50**(5), 1655–89.

BIS (1999): *Market Liquidity: Research Findings and Selected Policy Implications.* number 11 *in* CGFS Papers. Bank for International Settlements.

Bloomfield, R., Maureen, O. and Saar, G. (2005): The "make or take" decision in an electronic market: Evidence on the evolution of liquidity. *Journal of Financial Economics* **75**(1), 165–199.

Bouchaud, J.-P. and Potters, M. (2002): More statistical properties of order books and price impact. *Physica A: Statistical Mechanics and its Applications* **324**(1), 133–140.

Coppejans, M., Domowitz, I. and Madhavan, A. (2004): Resiliency in an Automated Auction.

Degryse, H., De Jong, F., van Ravenswaaij, M. and Wuyts, G. (2005): Aggressive Orders and the Resiliency of a Limit Order Market. *Review of Finance* **9**(2), 201–242.

Dong, J., Kempf, A. and Yadav, P. K. (2007): Resiliency, the Neglected Dimension of Market Liquidity: Empirical Evidence from the New York Stock Exchange. Technical report.

Dufour, A. R. and Engle, R. (2000): Time and the price impact of a trade. *Journal of Finance* **55**, 2467–2498.

Easley, D. and O'Hara, M. (1992): Time and the Process of Security Price Adjustment. *Journal of Finance* **47**, 557–605.

Engle, R. F. and Patton, A. J. (2004): Impacts of trades in an error correction model of quote prices. *Journal of Financial Markets* **71**(1), 1–25.

Escribano, A. and Pascual, R. (2006): Asymmetries in bid and ask responses to innovation in the trading process. *Empirical Economics* **30**, 913–946.

Foucault, T. (1994): Price formation and order placement strategies in a dynamic order driven market. Economics Working Papers 99. Department of Economics and Business, Universitat Pompeu Fabra.

Foucault, T. (1999): Order flow composition and trading costs in a dynamic limit order market1. *Journal of Financial Markets* **2**(2), 99–134.

Foucault, T., Kadan, O. and Kandel, E. (2005): Limit Order Book as a Market for Liquidity. *Review of Financial Studies* **18**(4), 1171–1217.

Foucault, T., Pagano, M. and Roell, A. (2013): *Market Liquidity: Theory, Evidence, and Policy.* number 9780199936243 *in* OUP Catalogue. Oxford University Press.

Garbade, K. D. (1982): *Pricing Corporate Securities as Contingent Claims.* MIT.

Glosten, L. R. and Milgrom, P. R. (1985): Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics* **14**(1), 71–100.

Goettler, R. L., Parlour, C. A. and Rajan, U. (2005): Equilibrium in a Dynamic Limit Order Market. *Journal of Finance* **60**(5), 2149–2192.

Gomber, P. and Schweickert, U. (2002): The Market Impact - Liquidity Measure in Electronic Securities Trading. Working paper.

Gomber, P., Schweickert, U. and Theissen, E. (2011): Liquidity dynamics in an electronic open limit order book: An event study approach. CFR Working Papers 11-14. University of Cologne, Centre for Financial Research (CFR).

Griffiths, M. D., Smith, B. F., Turnbull, D. A. S. and White, R. W. (2000): The costs and determinants of order aggressiveness. *Journal of Financial Economics* **56**(1), 65–88.

Harris, L. (1990): Statistical Properties of the Roll Serial Covariance Bid/Ask Spread Estimator. *Journal of Finance* **45**(2), 579–90.

Harris, L. E. (2003): *Trading and Exchanges: Market Microstructure for Practitioners.* Oxford University Press.

Hasbrouck, J. (1991): Measuring the Information Content of Stock Trades. *Journal of Finance* **46**(1), 179–207.

Hendershott, T., Jones, C. M. and Menkveld, A. (2011): Does Algorithmic Trading Improve Liquidity?. *Journal of Finance* **66**(1), 1–33.

Hmaied, D. M., Grar, A. and Sioud, O. B. (2006): Dynamics of Market Liquidity of Tunisian Stocks: An Analysis of Market Resiliency.

Kaniel, R. and Liu, H. (2006): So What Orders Do Informed Traders Use?. *The Journal of Business* **79**(4), 1867–1914.

Kutas, G. and Végh, R. (2005): A Budapesti Likviditási Mérték bevezetéséről. *Közgazdasági Szemle* **52**, 686–711.

Kyle, A. S. (1985): Continuous Auctions and Insider Trading. *Econometrica* **53**(6), 1315–35.

Large, J. (2007): Measuring the resiliency of an electronic limit order book. *Journal of Financial Markets* **10**(1), 1–25.

Large, J. (2009): A market-clearing role for inefficiency on a limit order book. *Journal of Financial Economics* **91**(1), 102–117.

Lillo, F., Farmer, J. and Mantegna, R. (2003): Master curve for price impact function. Nature, Vol. 421, pp. 129-130.. *Nature* **421**, 129–130.

Lybek, T. and Sarr, A. (2002): Measuring Liquidity in Financial Markets. IMF Working Papers 02/232. International Monetary Fund.

Muranaga, J. (2005): Dynamics of market liquidity of Japanese stocks: An analysis of tick-by-tick data of the Tokyo Stock Exchange. Technical report.

Nigmatullin, E., Tyurin, K. and Yin, H. (2007): Heterogeneous VAR Dynamics of Limit Order Book Depth, Trade Imbalance, and Volatility on the NYSE.

Parlour, C. A. (1998): Price dynamics in limit order markets. *Review of Financial Studies* **111**(4), 789–816.

Ranaldo, A. (2004): Order aggressiveness in limit order book markets. *Journal of Financial Markets* **7**(1), 53–74.

Rosu, I. (2009): A Dynamic Model of the Limit Order Book. *Review of Financial Studies* **22**(11), 4601–4641.

Rosu, I. (2015): Liquidity and Information in Order Driven Markets . Working paper. Department of Finance.

Weber, P. and Rosenow, B. (2005): Order book approach to price impact. *Quantitative Finance* **5**(4), 357–364.

Wuyts, G. (2011): The impact of aggressive orders in an order driven market: a simulation approach.

7 Appendix A

7.1 Table 1

Note: The table gathers the number and value of orders in the period between 02/09/2013 and 31/10/2013 for tickers OTP and MOL. The columns detail the means, medians and standard deviations, minimum and maximum number of a trading event, and means, medians and standard deviation of values in the observed period. Values are demoninated in EUR and converted from HUF (1 EUR was appox. 300 HUF).

Table 1: Summary stats: number of orders on a day (43 days)

	Number of transactions					Value of Transactions (EUR)		
OTP	mean	median	sd	min	max	mean	median	sd
transactions	717.8	669	201.7	324	1,324	13,515.9	5,469.1	39,599.7
limitbid	1,116.2	1,049	381.8	518	2,249	9,948.7	4,403.0	24,156.5
limitask	1,001.2	975	310.7	355	1,815	10,615.6	4,379.0	26,627.6
marketbuy	333.9	318	101.4	136	587	14,648.9	5,888.9	42,109.9
marketsell	382.2	350	124.1	186	759	12,383.5	4,859.3	36,962.0
cancelbid	525.8	474	239.4	236	1,388	11,911.2	4,295.0	46,539.7
cancelask	459.4	407	183.0	162	924	12,507.4	3,346.3	93,504.9
MOL	mean	median	sd	min	max	mean	median	sd
transactions	385.2	279	310.6	119	1,611	9,848.6	4,505.6	23,085.6
limitbid	633.8	535	382.8	241	2,149	6,077.1	2,475.0	13,294.7
limitask	585.2	450	365.4	185	1,775	7,046.0	3,812.7	15,145.5
marketbuy	193.7	132	169.1	45	888	9,394.2	4,401.5	22,548.4
marketsell	190.8	135	145.1	66	719	10,176.4	4,618.5	23,003.2
cancelbid	267.7	246	116.7	89	557	7,163.2	2,330.4	39,471.5
cancelask	317.8	250	213.1	69	924	7,076.2	2,599.1	30,175.1

7.2 Table 2

Note: The table summarizes the elapsed time between the same type of orders in the period between 02/09/2013 and 31/10/2013 for tickers OTP and MOL. The columns detail the specific order type. Rows $t01$-$t16$ denote half hour sessions of the trading day from 9:00 to 17:00. Means and medians for the entire day are also reported. Last two rows document the durations of market and limit submissions and limit cancellations.

Table 2: Time elapsed between the same types of orders (seconds)

	OTP						MOL					
Periods	mbuy	msell	lbid	lask	cbid	cask	mbuy	msell	lbid	lask	cbid	cask
t01	36.7	34.5	11.5	12.1	30.8	32.8	78.0	80.4	22.9	26.9	60.2	61.3
t02	65.4	63.2	19.8	20.8	47.1	50.4	118.2	111.5	35.7	39.2	83.9	87.3
t03	74.1	64.1	22.9	23.2	49.2	53.7	131.5	111.8	39.3	51.4	93.5	102.4
t04	86.1	78.8	29.1	28.6	61.2	66.9	140.2	156.6	45.0	50.7	109.1	98.9
t05	100.7	90.1	30.7	33.0	67.7	72.8	170.0	177.9	56.5	61.3	140.7	105.4
t06	128.2	105.6	33.9	43.2	65.2	101.3	239.0	193.1	68.5	73.1	151.6	137.7
t07	142.5	124.8	36.5	49.1	69.3	108.7	222.0	222.5	68.9	70.0	161.9	126.6
t08	124.2	135.6	39.1	50.4	69.2	112.4	164.6	163.5	61.1	57.1	150.9	92.8
t09	122.1	105.4	37.6	40.5	72.2	79.2	219.8	224.0	60.4	68.6	146.2	111.0
t10	154.6	130.6	42.7	48.9	82.2	88.8	173.3	235.5	61.9	60.7	159.3	102.6
t11	156.4	141.6	38.1	44.3	72.6	74.8	210.0	215.5	62.2	68.7	138.4	136.2
t12	103.5	99.3	31.0	38.8	63.8	79.9	175.5	179.1	46.9	54.2	100.3	89.8
t13	96.1	77.7	28.1	30.0	56.5	67.4	163.0	177.2	51.2	55.7	120.3	95.3
t14	79.8	60.0	24.5	26.9	55.5	52.9	135.4	122.8	45.1	40.0	109.4	72.1
t15	73.8	56.5	20.7	25.5	44.8	48.9	124.8	154.9	42.5	42.5	91.2	72.9
t16	46.9	40.6	16.1	17.5	32.1	35.2	85.1	87.9	26.4	29.5	60.6	50.6
Overall												
Mean	85.9	75.0	25.7	28.7	54.6	62.5	147.4	149.7	45.3	49.0	107.4	90.3
Median	25.0	26.0	10.0	12.0	22.0	23.0	37.0	35.0	16.0	17.0	38.0	26.0

Overall	MO (OTP)	LO (OTP)	CO (OTP)	MO (MOL)	LO (MOL)	CO (MOL)
Mean	40.0	58.2	123.4	74.4	100.4	197.7
Median	13	6	13	18	9	19

7.3 Table 3

Note: The table reports the statistical properites of cost of round trip indicators. LP or liquidity premium means the relative half spread (half spread over midprice). APM or adverse price movement means the relative costs of a transaction with a specified volume (EUR) over the best bid or ask level. Statistics are calculated in transaction time. (1 EUR equals approximately 300 HUF.)

Table 3: Cost of rount trip indicators: summary statistics

OTP, N=30,866	mean	sd	min	p25	median	p75	max
lp	5.185	3.66	1.096	2.355	4.59	6.673	43.789
apm bid: €1,000	0.246	1.292	0	0	0	0	43.836
apm bid: €3,000	0.584	1.967	0	0	0	0	51.287
apm bid: €5,000	0.888	2.389	0	0	0	0.590	52.776
apm bid: €10,000	1.624	3.179	0	0	0	2.001	63.123
apm bid: €20,000	2.977	4.345	0	0	1.612	4.125	95.346
apm bid: €40,000	5.451	6.031	0	1.503	3.781	7.691	123.708
apm bid: €70,000	8.882	8.13	0	3.418	7.037	12.05	147.841
apm ask: €1,000	0.278	1.343	0	0	0	0	39.715
apm ask: €3,000	0.701	2.133	0	0	0	0	47.953
apm ask: €5,000	1.045	2.608	0	0	0	0.945	49.948
apm ask: €10,000	1.826	3.356	0	0	0.101	2.166	53.779
apm ask: €20,000	3.228	4.383	0	0	1.806	4.460	84.089
apm ask: €40,000	5.678	5.897	0	1.637	4.024	8.049	107.239
apm ask: €70,000	8.996	7.864	0	3.476	7.165	12.365	123.712
MOL, N=16,563	mean	sd	min	p25	median	p75	max
lp	8.055	5.998	1.499	3.348	6.57	10.861	49.044
apm bid: €1,000	0.555	2.2	0	0	0	0	48.93
apm bid: €3,000	1.382	3.544	0	0	0	1.118	57.893
apm bid: €5,000	2.082	4.305	0	0	0	2.530	60.848
apm bid: €10,000	3.698	5.671	0	0	1.757	4.928	64.891
apm bid: €20,000	6.605	7.683	0	1.291	4.12	9.335	90.446
apm bid: €40,000	11.929	10.724	0	4.433	9.139	16.354	110.992
apm bid: €70,000	19.303	14.444	0	9.052	16.346	25.806	141.181
apm ask: €1,000	0.423	2.029	0	0	0	0	59.183
apm ask: €3,000	1.157	3.374	0	0	0	0.340	63.4
apm ask: €5,000	1.814	4.19	0	0	0	2.035	67.692
apm ask: €10,000	3.421	5.721	0	0	1.28	4.438	75.067
apm ask: €20,000	6.469	8.078	0	0.972	3.648	8.946	97.935
apm ask: €40,000	11.968	11.505	0	4.039	8.643	16.324	114.001
apm ask: €70,000	19.529	15.189	0	8.851	15.862	26.042	139.581

7.4 Table 4

Note: This table details the estimated coefficients of the VAR system for ticker OTP. Variables dlogbid and dlogask are multiplied by 1000 for better visibilitiy of the coefficients. Level of significance is calculated based on Newey-West adjusted t-values. Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 4: Cost of trade and market orders.

Panel A. Cost of trade and market orders. Ticker: OTP

variables	dlogask		dlogbid		a		b		q	
dlogask.l1	-0.178	***	0.079	***	0.202	*	-0.015		-0.954	***
dlogbid.l1	0.091	***	-0.144	***	-0.07		-0.142		-0.426	***
a.l1	0.025	***	0.012	***	0.691	***	0.07	***	0.078	***
b.l1	-0.008	***	-0.019	***	0.051	***	0.712	***	-0.051	***
q.l1	0.008	***	0.006	***	-0.022	***	0.013	.	0.201	***
dlogask.l2	-0.087	***	0.042	***	0.072		-0.044		-0.343	***
dlogbid.l2	0.067	***	-0.064	***	0.009		0.112		0.035	
a.l2	-0.004	*	-0.005	**	0.076	***	-0.018		-0.033	**
b.l2	0.002		0.003	*	-0.003		0.051	***	0.013	
q.l2	0.004	***	0.004	***	-0.013	*	0.013	*	0.115	***
dlogask.l3	-0.035	**	0.038	***	-0.066		-0.187	*	-0.168	*
dlogbid.l3	0.071	***	-0.034	**	-0.115		0.288	**	0.068	
a.l3	-0.002		0		0.028	*	0		-0.019	.
b.l3	-0.001		0.002		0.012		0.042	**	0.008	
q.l3	0.001		0.002	*	-0.004		0.011	*	0.076	***
dlogask.l4	-0.042	***	0.016		0.063		-0.003		-0.042	
dlogbid.l4	0.015		-0.048	***	0.07		0.116		-0.015	
a.l4	-0.007	***	-0.001		0.069	***	-0.009		-0.014	.
b.l4	0.001		0.003	*	-0.013		0.037	**	0.007	
q.l4	0.003	***	0.003	***	-0.013	*	0.002		0.053	***
t01	0.096	***	-0.051	**	0.375	**	0.693	***	0.304	**
t02	0.062	***	-0.048	***	0.079		0.116		0.377	**
t03	0.051	***	-0.065	***	0.231	*	0.184	.	0.249	.
t04	0.069	***	-0.044	**	-0.091		0.058		0.308	*
t05	0.06	***	-0.059	***	0.016		-0.064		0.452	**
t06	0.033	*	-0.033	*	0.024		-0.079		0.299	.
t07	0.065	***	-0.032	*	-0.314	**	-0.037		0.556	**
t08	0.035	*	-0.017		-0.09		0.024		0.715	***
t09	0.041	**	-0.044	**	-0.013		-0.161		0.329	.
t10	0.043	**	-0.062	***	-0.135		-0.207	.	0.398	*
t11	0.056	***	-0.024		-0.029		-0.02		0.434	*
t12	0.07	***	-0.032	*	-0.008		-0.055		0.632	***
t13	0.044	**	-0.06	***	0.009		0.076		0.132	
t14	0.053	***	-0.048	***	0.04		-0.09		0.067	
t15	0.064	***	-0.035	**	-0.051		0.003		0.049	
logdur.MO	-0.045	***	0.034	***	-0.221	***	-0.386	***	-0.137	**
logdur.LO	0.047	***	-0.048	***	0.111	***	0.214	***	-0.166	***
lag.logspread	-94.47	***	109.585	***	24.41		9.508		117.081	*

Note: This table details the estimated coefficients of the VAR system for ticker MOL. Variables dlogbid and dlogask are multiplied by 1000 for better visibilitiy of the coefficients. Level of significance is calculated based on Newey-West adjusted t-values. Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Panel B. Cost of trade and market orders. Ticker: MOL

variables	dlogask		dlogbid		a		b		q	
dlogask.l1	-0.212	***	0.057	***	0.428	**	-0.264	*	-0.496	***
dlogbid.l1	0.098	***	-0.178	***	0.03		0.047		-0.304	***
a.l1	0.02	***	0.007	***	0.748	***	0.057	***	0.023	***
b.l1	-0.01	***	-0.018	***	0.069	***	0.728	***	-0.018	**
q.l1	0.01	***	0.013	***	-0.049	**	0.005		0.215	***
dlogask.l2	-0.082	***	0.041	**	-0.134		0.036		-0.204	***
dlogbid.l2	0.028	*	-0.058	***	0.155		-0.037		-0.082	
a.l2	-0.008	***	-0.003	.	0.071	***	-0.035	*	-0.004	
b.l2	0.005	.	0.003		-0.024		0.08	***	0.011	
q.l2	0.01	***	0.008	***	-0.034	*	0.034	*	0.129	***
dlogask.l3	-0.038	**	0.019	.	0.05		0.029		-0.103	*
dlogbid.l3	0.031	**	-0.017		0.001		0.051		-0.029	
a.l3	-0.003	*	0.001		0.057	***	0.014		-0.013	**
b.l3	0.001		0.005	**	-0.005		0.067	***	0.001	
q.l3	0.005	**	0.002		-0.028	.	0.02		0.089	***
t01	0.264	***	-0.08		1.149	***	1.77	***	0.041	
t02	0.12	***	-0.122	***	-0.146		-0.022		-0.158	
t03	0.084	**	-0.187	***	-0.229		0.154		-0.446	**
t04	0.124	***	-0.077	**	-0.582	*	0.073		0.096	
t05	0.143	***	-0.063	*	-0.31		0.335		0.053	
t06	0.087	**	-0.067	*	-0.267		0.464		-0.148	
t07	0.076	*	-0.14	***	-0.187		-0.216		-0.21	
t08	0.039		-0.132	***	0.235		-0.266		-0.331	*
t09	0.105	***	-0.069	*	-0.114		-0.023		-0.029	
t10	0.134	***	-0.066	*	-0.37		-0.077		0.015	
t11	0.106	**	-0.073	**	-0.576	.	-0.241		0.118	
t12	0.142	***	-0.081	*	-0.551	*	0.228		0.073	
t13	0.131	***	-0.085	**	-0.256		-0.262		-0.084	
t14	0.097	***	-0.136	***	-0.018		-0.121		-0.076	
t15	0.095	***	-0.065	**	-0.486	*	0.032		0.078	
logdur.MO	-0.074	***	0.049	***	-0.427	***	-0.435	***	-0.089	*
logdur.LO	0.08	***	-0.063	***	0.257	***	0.212	***	0.093	**
lag.logspread	-129.268	***	111.29	***	99.007		26.179		-29.223	

7.5 Table 5

Note: The table shows the three most significant components of bid and ask adverse price movement incremental variables. The components are extracted by principal components analysis. APM or adverse price movement means the relative costs of a transaction with a specified volume (EUR) over the best bid or ask level. Statistics are calculated in transaction time.

Table 5: Decomposition of the limit order book structure

Panel A. Bid and ask side loadings

OTP						
APM diffs (levels in EUR)	Bid Comp.1	Bid Comp.2	Bid Comp.3	Ask Comp.1	Ask Comp.2	Ask Comp.3
APM(1000)	0.102	-0.284	-0.729	0.128	-0.267	-0.739
APM(3000)-APM(1000)	0.273	-0.507	-0.291	0.305	-0.494	-0.279
APM(5000)-APM(3000)	0.396	-0.455	0.190	0.405	-0.440	0.191
APM(10000)-APM(5000)	0.464	-0.187	0.392	0.467	-0.180	0.408
APM(20000)-APM(10000)	0.481	0.185	0.204	0.466	0.223	0.199
APM(40000)-APM(20000)	0.439	0.443	-0.187	0.424	0.465	-0.174
APM(70000)-APM(40000)	0.346	0.436	-0.342	0.334	0.438	-0.321
MOL						
APM diffs (levels in EUR)	Bid Comp.1	Bid Comp.2	Bid Comp.3	Ask Comp.1	Ask Comp.2	Ask Comp.3
APM(1000)	0.124	-0.369	-0.642	0.127	-0.320	-0.704
APM(3000)-APM(1000)	0.275	-0.523	-0.287	0.281	-0.519	-0.269
APM(5000)-APM(3000)	0.399	-0.425	0.243	0.379	-0.448	0.218
APM(10000)-APM(5000)	0.466	-0.138	0.449	0.464	-0.152	0.427
APM(20000)-APM(10000)	0.478	0.212	0.184	0.486	0.198	0.186
APM(40000)-APM(20000)	0.435	0.421	-0.235	0.448	0.419	-0.199
APM(70000)-APM(40000)	0.338	0.410	-0.395	0.328	0.436	-0.357

Panel B. Explanatory power of the components

Comp.		1	2	3	4	5	6	
OTP	ask	36.16%	23.65%	15.54%	10.77%	6.73%	4.21%	2.94%
	bid	37.39%	22.59%	15.43%	10.81%	6.88%	4.08%	2.82%
MOL	ask	36.19%	23.77%	15.33%	10.65%	6.67%	4.36%	3.02%
	bid	36.59%	23.30%	15.48%	10.56%	6.54%	4.35%	3.19%

7.6 Table 6

Note: This table details the estimated coefficients of the VAR system for ticker OTP. Variables dlogbid and dlogask are multiplied by 1000 for better visibilitiy of the coefficients. Level of significance is calculated based on Newey-West adjusted t-values. Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table 6: Cost of trade structure and market orders.

Panel A. Cost of trade structure and market orders. Ticker: OTP

variables	dlogask		dlogbid		a1		b1		a2		b2		a3		b3		q	
dlogask.l1	-0.14	***	0.059	***	0.038		0.031		-0.015		0.003		0.019		0.009		-0.885	***
dlogbid.l1	0.05	***	-0.127	***	-0.001		-0.054	*	-0.005		0.003		-0.021		-0.001		-0.549	***
a1.l1	0.119	***	0.056	***	0.615	***	0.031	*	-0.045	***	-0.003		0.039	*	0.02	.	0.402	***
b1.l1	-0.041	***	-0.093	***	0.023	*	0.643	***	-0.002		0.039	*	0.01		0.047	**	-0.256	***
a2.l1	0.002		-0.002		-0.19	***	0.012		0.459	***	-0.002		-0.021	*	-0.002		-0.312	***
b2.l1	0.009	*	0.026	***	-0.017	*	0.209	***	0		0.399	***	0.003		0.051	***	-0.186	***
a3.l1	0.036	***	0.014	**	0.083	***	0.008		-0.155	***	-0.003		0.337	***	0.001		-0.037	
b3.l1	-0.004		-0.034	***	0.004		0.086	***	-0.006		0.125	***	0.023	**	0.327	***	0.028	
q.l1	0.008	***	0.006	***	-0.006	***	0.001		-0.001		0.002		-0.001		0.001		0.208	***
dlogask.l2	-0.056	***	0.02		-0.004		-0.01		-0.025		-0.039	.	-0.018		0.015		-0.312	***
dlogbid.l2	0.034	**	-0.044	***	0.046	*	0.024		0.054	**	-0.015		-0.022		0.01		-0.015	
a1.l2	-0.015		-0.022	**	0.057	***	-0.016		-0.023	.	-0.013		-0.013		0.007		-0.166	**
b1.l2	0.006		0.012	.	0.002		0.042	*	-0.013		0.022		-0.004		-0.006		0.071	
a2.l2	0.012	.	0.014	**	0.01		0.005		0.1	***	0.01		-0.003		0.009		0.136	***
b2.l2	0.003		0.006		0.007		-0.004		0		0.086	***	-0.003		0.013		0.091	*
a3.l2	-0.005		-0.003		0.004		0.006		0.004		-0.003		0.073	***	0.005		0.008	
b3.l2	-0.009		-0.003		0.014		-0.023		0.004		0.037	**	0.002		0.071	***	-0.035	
q.l2	0.005	***	0.004	***	-0.004	**	0.002		0.002	.	0.001		0		0		0.123	***
dlogask.l3	-0.029	**	0.022	*	0.013		-0.02		-0.033	.	-0.001		0.008		-0.018		-0.203	**
dlogbid.l3	0.044	***	-0.019	*	-0.022		0.034		0.023		-0.011		0.006		-0.008		0.032	
a1.l3	-0.027	***	0.001		0.056	***	0.02		-0.025	**	0.006		0.024	**	-0.016		-0.146	***
b1.l3	-0.002		0.007		0.019	*	0.036	*	0.02	*	0.042	***	0.004		0.015	.	0.066	.
a2.l3	0.032	***	0.008	.	-0.037	***	-0.007		0.061	***	0		-0.022	*	0.003		0.163	***
b2.l3	0.005		0.012	*	-0.013		0.016		0.004		0.057	***	-0.008		0.005		0.062	.
a3.l3	-0.006		0.007		0.015		0.013		0.003		-0.002		0.059	***	0		-0.028	
b3.l3	-0.001		0.005		0.012		0.022		0.036	**	0.011		0.004		0.02	*	-0.011	
q.l3	0.002	**	0.002	***	-0.001		0.002		0.001		0.001		-0.001		0.001		0.086	***
t01	0.084	***	-0.045	*	0.065	*	0.124	***	0.048	.	-0.034		0.019		0.018		0.313	**
t02	0.061	***	-0.041	**	-0.015		0.029		0		-0.022		-0.004		-0.031		0.401	**
t03	0.047	**	-0.059	***	0.028		0.034		0.015		-0.009		-0.011		-0.028		0.251	.
t04	0.065	***	-0.046	***	-0.04		-0.018		0.024		0.021		-0.01		-0.038	.	0.33	*
t05	0.057	***	-0.061	***	-0.029		-0.053	*	0.006		0.031		-0.007		-0.036	.	0.469	**
t06	0.025	.	-0.032	*	0.028		0.005		0.073	*	-0.009		0.022		-0.058	*	0.309	.
t07	0.063	***	-0.035	*	-0.073	*	-0.042		0.017		0.024		-0.045	*	-0.028		0.573	**
t08	0.029	.	-0.019		0.015		-0.027		0.042		0.004		-0.042	.	0.056	*	0.749	***
t09	0.041	**	-0.04	**	-0.031		-0.026		-0.011		-0.009		-0.004		-0.042	.	0.341	*
t10	0.049	**	-0.052	***	-0.09	**	-0.025		0.008		-0.048		0.033		-0.042		0.428	*
t11	0.06	***	-0.022		-0.034		-0.003		-0.012		0.007		-0.031		-0.055	*	0.446	*
t12	0.077	***	-0.023		-0.055	*	-0.009		-0.029		-0.035		-0.018		-0.004		0.662	***
t13	0.04	**	-0.058	***	-0.016		-0.006		0.031		-0.005		0.011		0.003		0.143	
t14	0.05	***	-0.047	***	-0.023		-0.039	.	0.019		0.003		0.028		-0.009		0.075	
t15	0.062	***	-0.035	**	-0.041	.	-0.025		0.001		0.016		0.001		-0.012		0.05	
logdur.MO	-0.047	***	0.035	***	0.007		-0.029	***	0.015	.	-0.012		0.003		-0.001		-0.137	**
logdur.LO	0.049	***	-0.048	***	-0.036	***	-0.008		-0.023	***	0.019	**	0.001		0.004		-0.168	***
lag.logspread	-92.557	***	105.642	***	83.548	***	61.151	***	13.598		-20.303	.	-4.379		7.607		99.736	*

Note: This table details the estimated coefficients of the VAR system for ticker OTP. Variables dlogbid and dlogask are multiplied by 1000 for better visibilitiy of the coefficients. Level of significance is calculated based on Newey-West adjusted t-values. Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Panel B. Cost of trade structure and market orders. Ticker: MOL

variables	dlogask		dlogbid		a1		b1		a2		b2		a3		b3		q	
dlogask.l1	-0.2	***	0.032	*	0.084	***	-0.022		-0.021		0.011		0.015		0.012		-0.49	***
dlogbid.l1	0.08	***	-0.163	***	-0.028		-0.036	.	0.029		0.046	*	-0.027		-0.009		-0.334	***
a1.l1	0.184	***	0.064	***	0.69	***	0.01		0.033	.	0.004		0.006		0.023	.	0.239	***
b1.l1	-0.079	***	-0.148	***	0.04	*	0.698	***	0		0.035	*	-0.003		-0.003		-0.168	***
a2.l1	-0.047	**	-0.014	.	0.238	***	-0.012		0.424	***	0.001		0.015		0.01		0.138	***
b2.l1	0.02	.	0.071	***	-0.013		0.234	***	0.02		0.487	***	-0.021		-0.01		-0.119	**
a3.l1	0.045	**	0.002		0.077	***	-0.004		0.193	***	-0.008		0.314	***	0.003		-0.047	
b3.l1	-0.038	***	-0.048	***	0.039	**	0.107	***	-0.014		0.187	***	-0.018	.	0.337	***	0.067	.
q.l1	0.01	***	0.013	***	-0.004		0.003		-0.003		-0.003		0.001		0.001		0.217	***
dlogask.l2	-0.082	***	0.017		0.001		-0.006		-0.01		0.003		0.006		0.007		-0.176	***
dlogbid.l2	0.021		-0.05	**	0.02		-0.007		-0.017		0.024		0.002		-0.014		-0.119	*
a1.l2	-0.06	**	-0.018		0.056	*	-0.021		0.03		0.012		0.019		-0.008		-0.035	
b1.l2	0.029		0.011		-0.027		0.036		0.016		0.019		0.008		0.039	*	0.099	
a2.l2	-0.027		-0.007		-0.004		-0.011		0.116	***	0		0.025	.	-0.011		-0.039	
b2.l2	0.001		0.003		-0.004		-0.027	.	0.001		0.075	***	0.001		0.046	**	0.056	
a3.l2	0		0.004		-0.034	*	-0.023	*	0.025		0.01		0.086	***	-0.011		0.072	.
b3.l2	-0.001		0.008		-0.004		0.002		0		0.005		0.018		0.102	***	-0.018	
q.l2	0.01	***	0.009	***	-0.004	.	0.003		0.002		0.002		-0.001		0.002		0.13	***
dlogask.l3	-0.035	*	0.017		0.006		0.016		0.01		-0.005		0.025	.	0.004		-0.098	*
dlogbid.l3	0.03	*	-0.015		-0.005		-0.005		-0.007		0.014		-0.015		-0.004		-0.023	
a1.l3	-0.003		0.013		0.026		0.034	**	0.017		-0.02		0.026	.	0.005		-0.118	**
b1.l3	0.007		0.027	*	0.011		0.04	*	-0.022	.	0.017		0.003		0.015		0.011	
a2.l3	-0.004		-0.007		-0.017		0.021	*	0.054	***	-0.014		0.035	**	-0.001		-0.123	***
b2.l3	0.007		0.016		0.011		-0.004		-0.019	.	0.048	***	-0.006		0.016		0.034	
a3.l3	-0.011		0.008		0.005		0.031	**	0.022		-0.017		0.063	***	0.004		-0.06	
b3.l3	-0.012		-0.004		0.015		-0.009		0.023	.	0.009		-0.007		0.066	***	0.007	
q.l3	0.004	*	0.001		-0.002		0.002		-0.003		-0.003		-0.001		0.001		0.087	***
t01	0.236	***	-0.059		0.107	*	0.14	**	-0.087	*	-0.069		0.021		0.089	*	0.021	
t02	0.105	***	-0.115	***	-0.042		-0.047		-0.037		0.007		0.01		-0.011		-0.159	
t03	0.077	**	-0.17	***	-0.069	*	-0.02		-0.019		-0.042		-0.004		0.026		-0.448	**
t04	0.102	***	-0.074	**	-0.051	.	-0.014		-0.053	.	0.021		-0.029		-0.035		0.1	
t05	0.135	***	-0.033		-0.06	.	0.085	*	-0.017		-0.081	*	0.006		-0.058	.	0.064	
t06	0.079	*	-0.062	.	-0.045		0.033		-0.02		0.04		-0.012		-0.038		-0.131	
t07	0.05		-0.14	***	0.022		-0.072	.	-0.048		0.008		-0.113	*	0.002		-0.229	
t08	0.047		-0.106	***	-0.045		-0.002		0.025		-0.014		0.059		-0.062	.	-0.306	.
t09	0.124	***	-0.03		-0.081	*	0.042		0.037		-0.079	.	-0.002		-0.029		-0.012	
t10	0.115	***	-0.053	.	-0.03		-0.014		-0.053		-0.031		-0.022		-0.018		0.016	
t11	0.08	*	-0.073	**	-0.027		-0.049		-0.076		0.021		-0.038		-0.04		0.118	
t12	0.122	***	-0.081	**	-0.07	*	0.002		-0.042		0.021		0.006		-0.064	*	0.08	
t13	0.117	***	-0.07	**	-0.046		-0.017		-0.036		-0.014		0.01		-0.076	**	-0.069	
t14	0.078	**	-0.127	***	0		-0.029		-0.021		0.015		-0.06	*	-0.059	*	-0.073	
t15	0.081	**	-0.067	**	-0.059	*	-0.032		-0.003		0.023		-0.025		-0.012		0.078	
logdur.MO	-0.078	***	0.053	***	-0.005		-0.004		-0.007		-0.016	.	0.005		0.004		-0.091	*
logdur.LO	0.083	***	-0.066	***	-0.021	**	-0.027	***	0.02	*	0.017	*	-0.001		0.005		0.092	**
lag.logspread	-121.769	***	102.703	***	58.002	***	46.392	***	-7.742		-1.196		2.631		2.999		-26.986	

7.7 Table 7

Note. This table gives a numerical example about a typical order book recovery process after a market buy. Only ask side of the limit order book is indicated in details. Four states: 1) original, 2) market buy, 3) new bid limit, 4) ask recovery.

Table 7: Example

	original	market buy	new bid limit	ask recovery
quote	volume	volume	volume	volume
110	500	500	500	1000
108	1000	1000	1000	3000
106	3000	3000	3000	3000
104	3000	3000	3000	1000
102	1000	1000	1000	1000
100	1000			
ask	100	102	102	102
mid	98	99	100	100
bid	96	96	98	98

8 Appendix B

8.1 Figure 1

Note: X axis shows the value (price $\times$ quantity) of a hypothetical trade. Y axis depicts the price divergence from the mid-price in basis points.

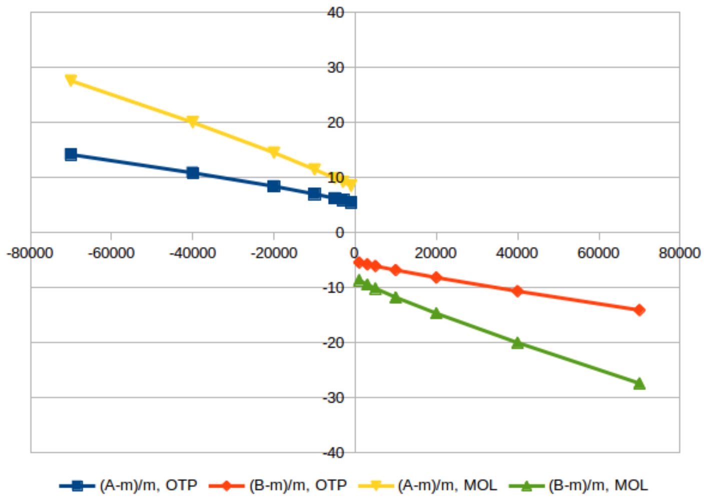
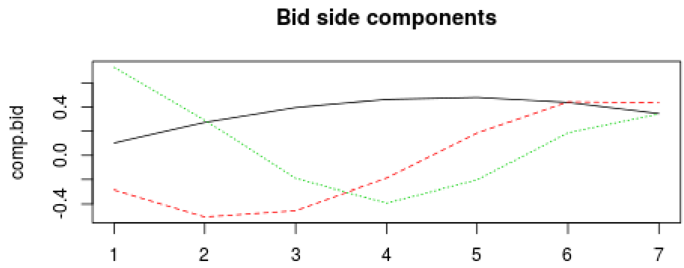


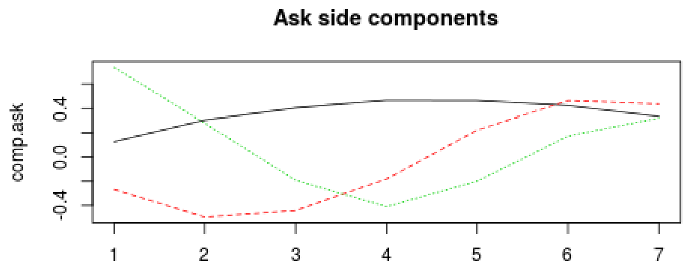
Figure 1: Distance from mid-price in basis point values. Tickers: OTP and MOL

8.2 Figure 2

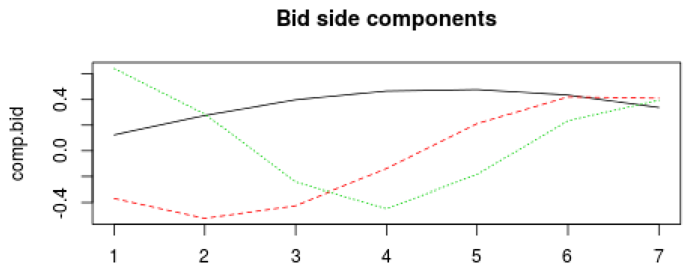
Note: The figures illustrate the three main components. X axis counts the APM levels. Y axis shows the loadings of the components.

OTP





MOL



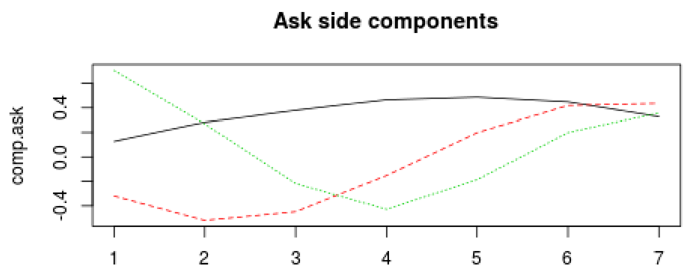
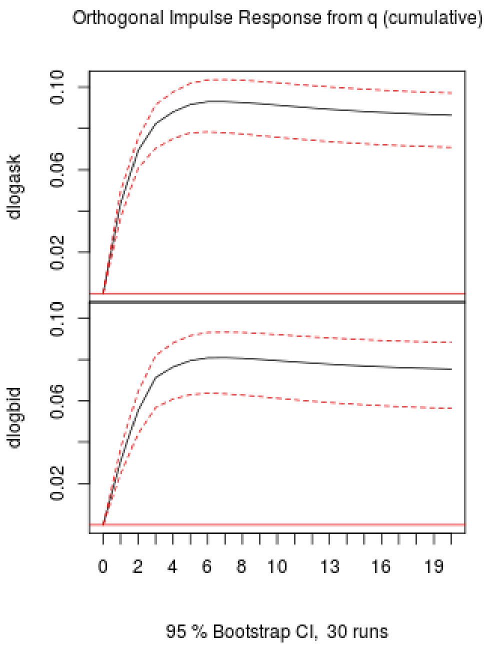


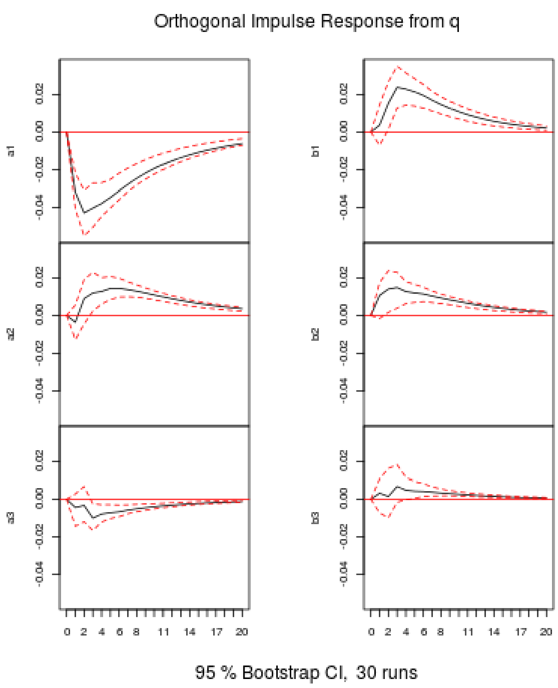
Figure 2: Principal components: visualisation. Tickers: OTP, MOL

8.3 Figure 3

Note: The figure shows the impulse responses of a normal buy trade. Size of shock is one standard deviation. Ticker: OTP.

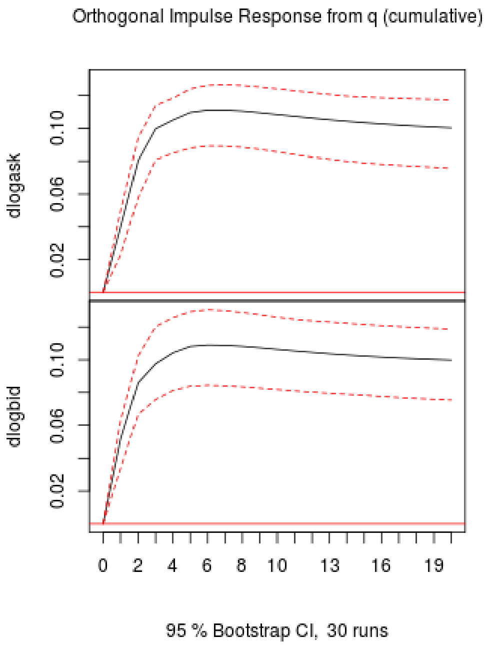
Figure 3: Impulse-response functions

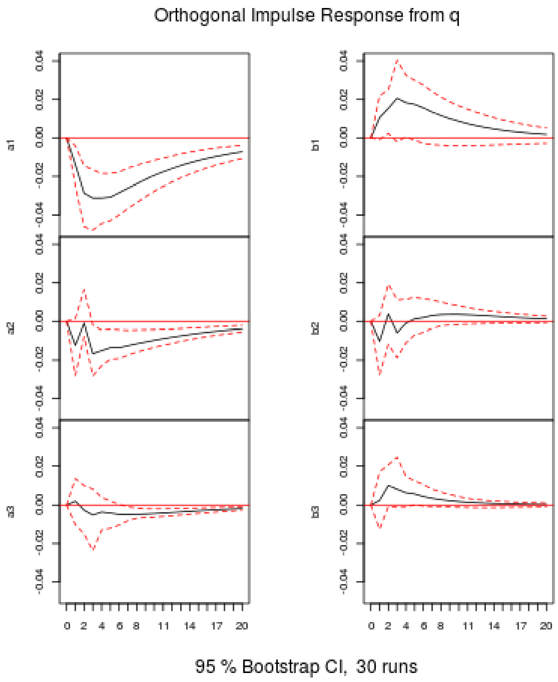




Impulse-response functions. Ticker: OTP

Note: The figure shows the impulse responses of a normal buy trade. Size of shock is one standard deviation. Ticker: MOL.



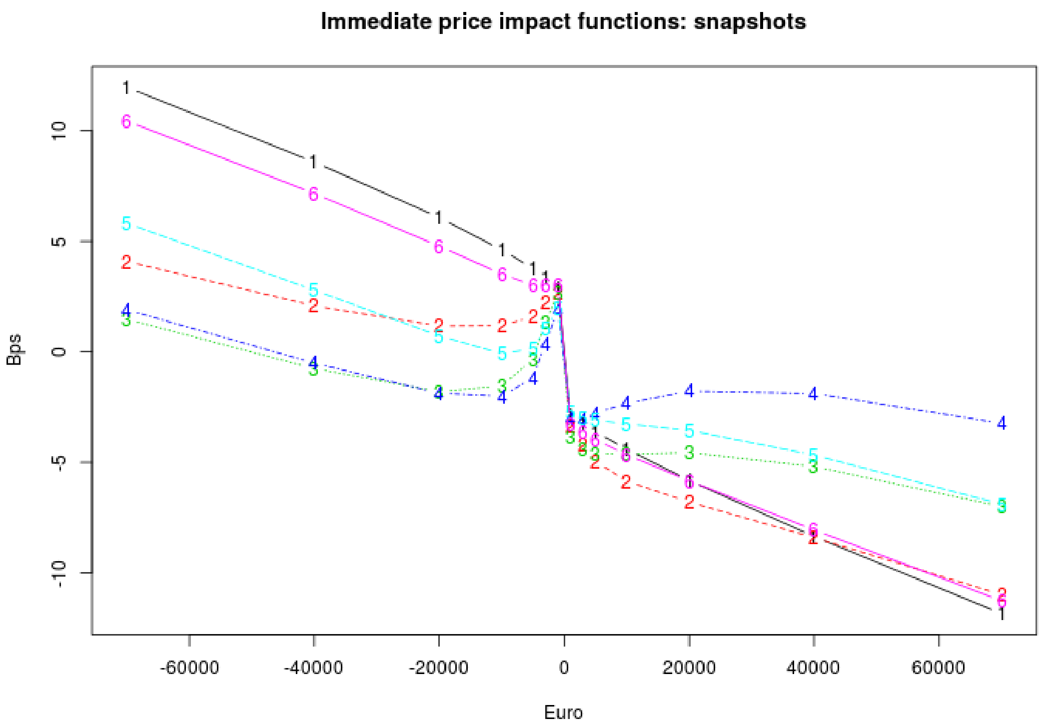


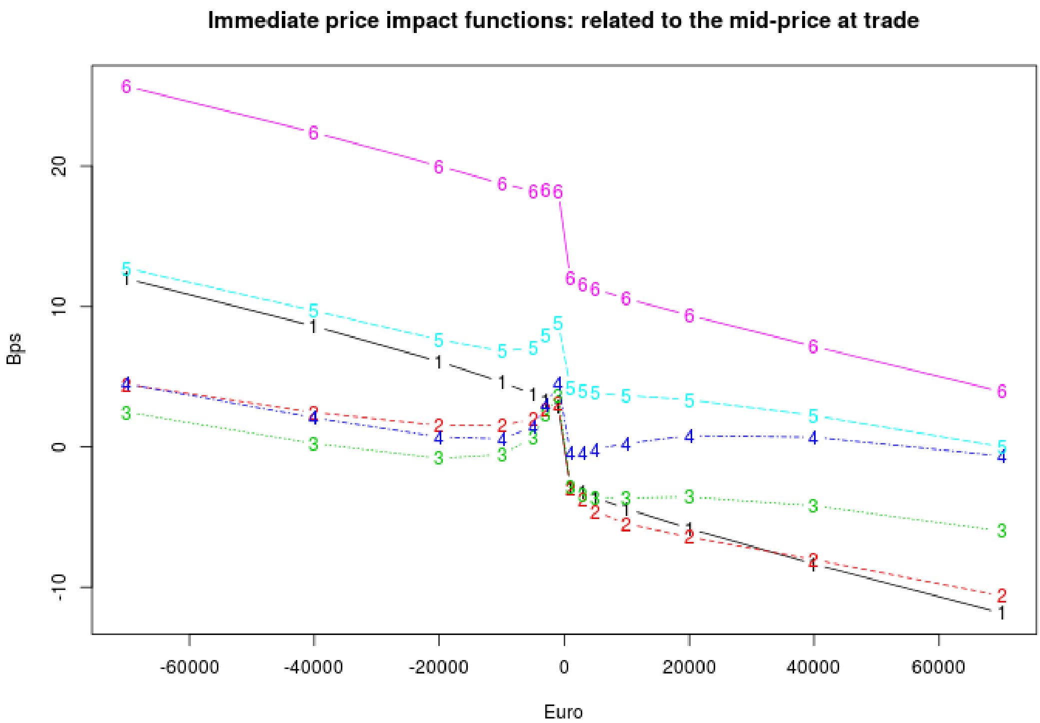
Impulse-response functions. Ticker: MOL

8.4 Figure 4

Note: The figure illustrate the price impact movements induced by a normal buy trade. Ticker: OTP.

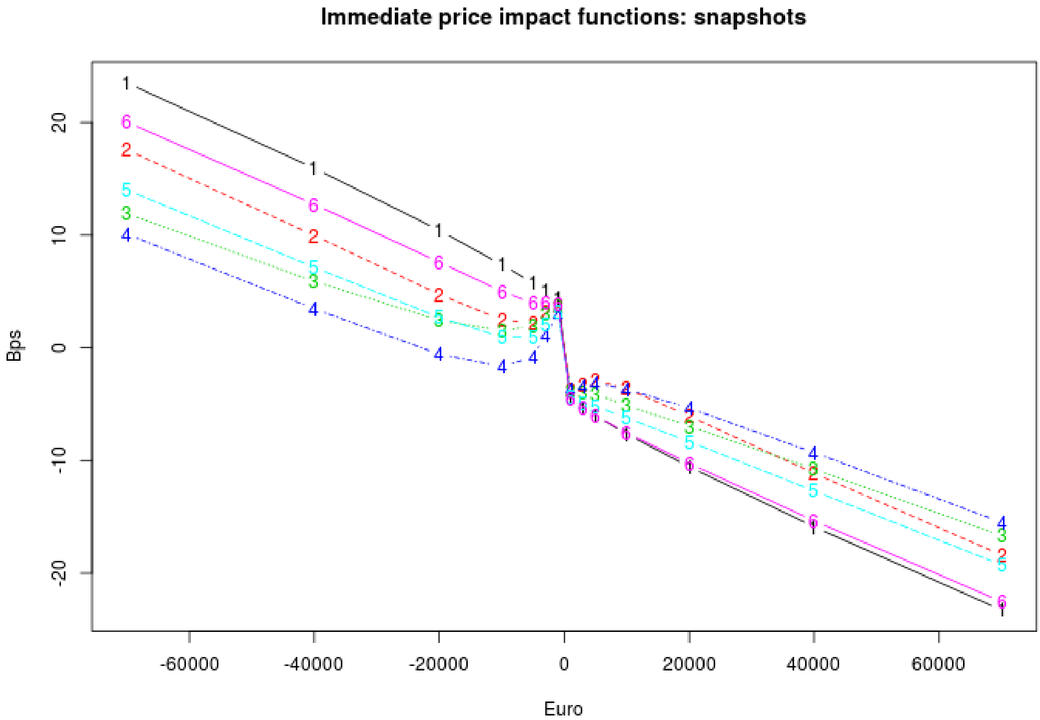
Figure 4: Illustration: Six steps of the immediate price impact function.

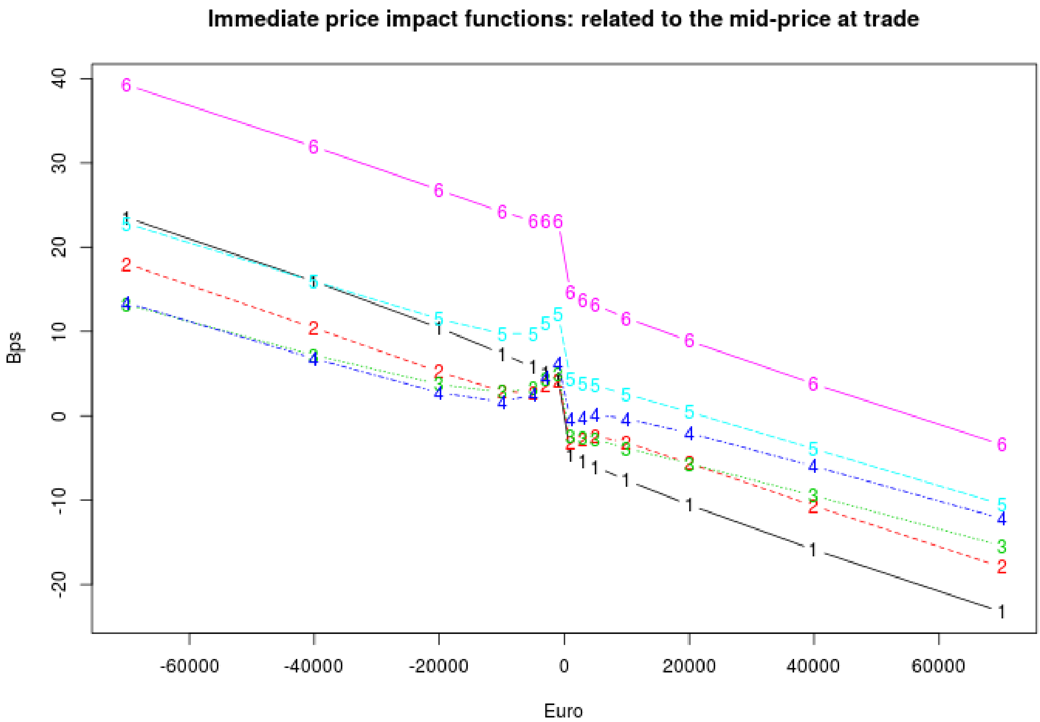




”Overstreched” movements. Ticker: OTP

Note: The figure illustrate the price impact movements induced by a normal buy trade. Ticker: MOL.



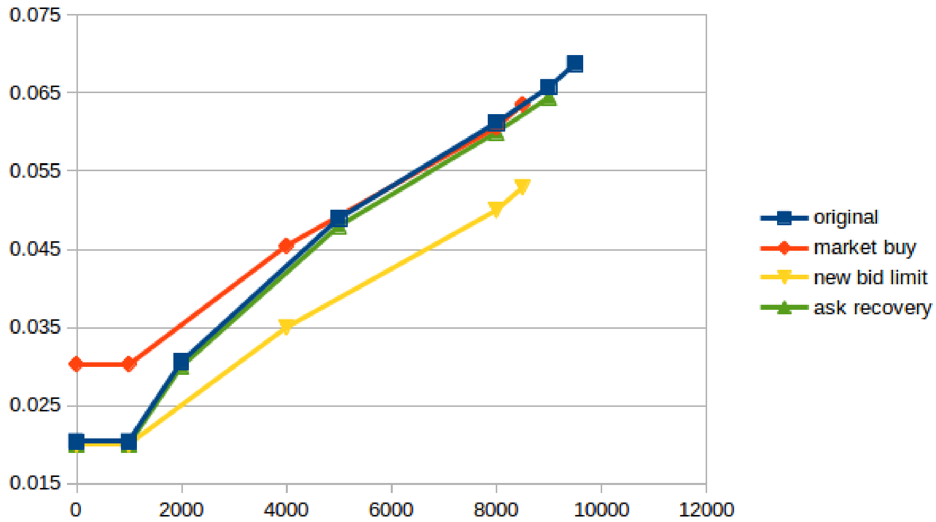


"Overstreched" movements. Ticker: MOL

8.5 Figure 5

Note: X axis shows the values of APM levels. Y axis shows the adverse price movement in basis points.

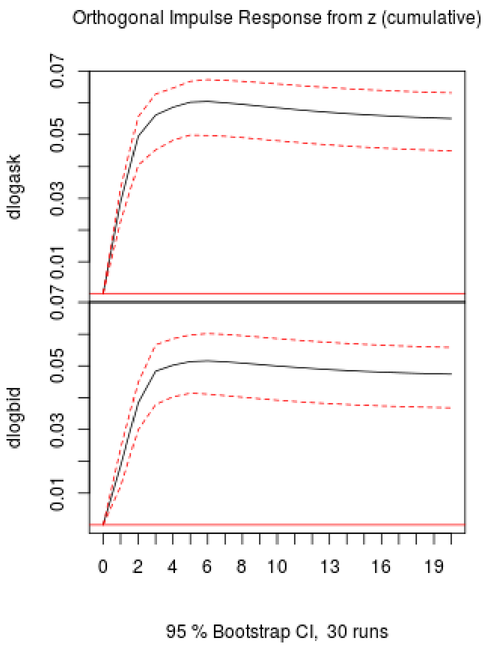
Figure 5: Example: order book dynamics

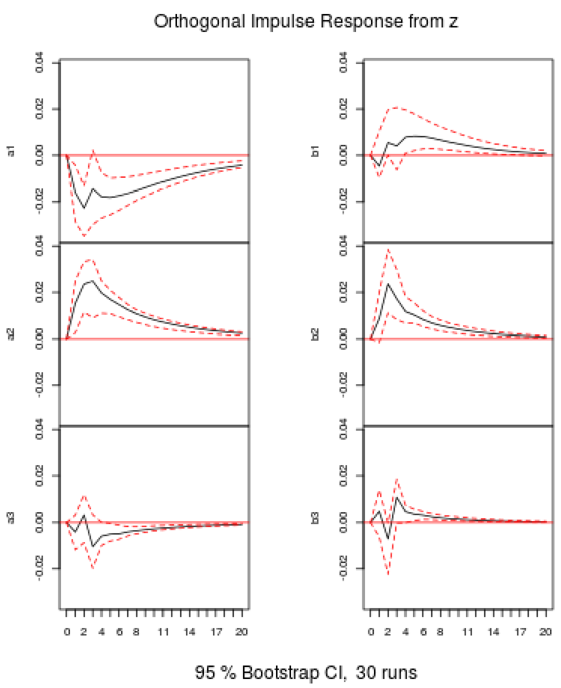


8.6 Figure 6

Note: The figure shows the impulse responses of an aggressive buy trade. Size of shock is one standard deviation. Ticker: OTP.

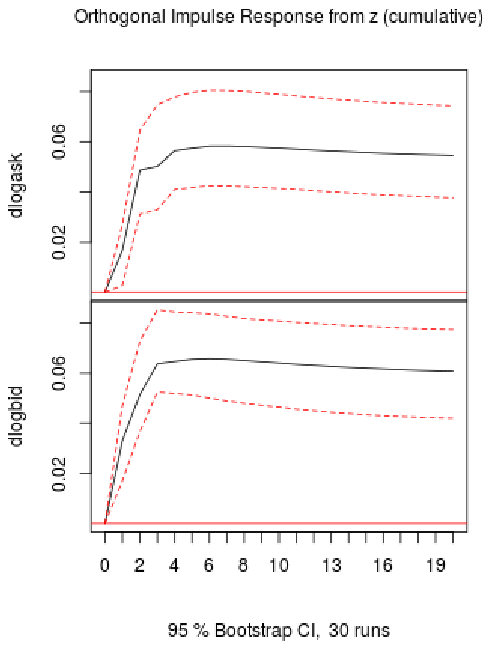
Figure 6: Impulse-response functions: aggressive market orders

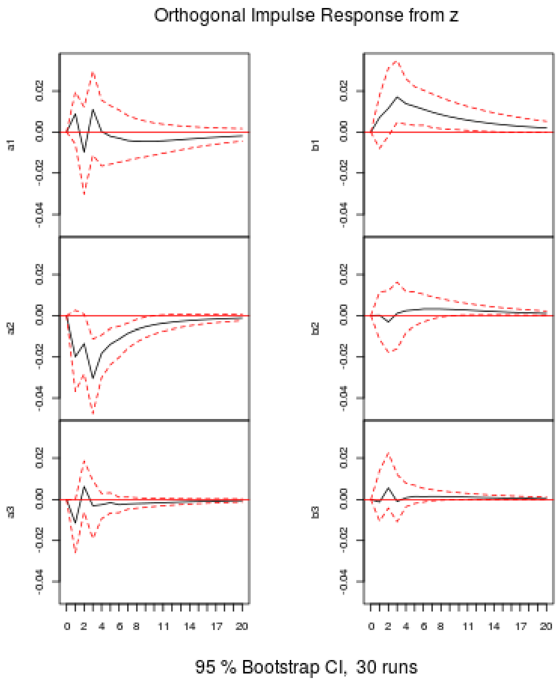




Impulse-response functions:aggressive market orders. Ticker: OTP

Note: The figure shows the impulse responses of an aggressive buy trade. Size of shock is one standard deviation. Ticker: MOL.



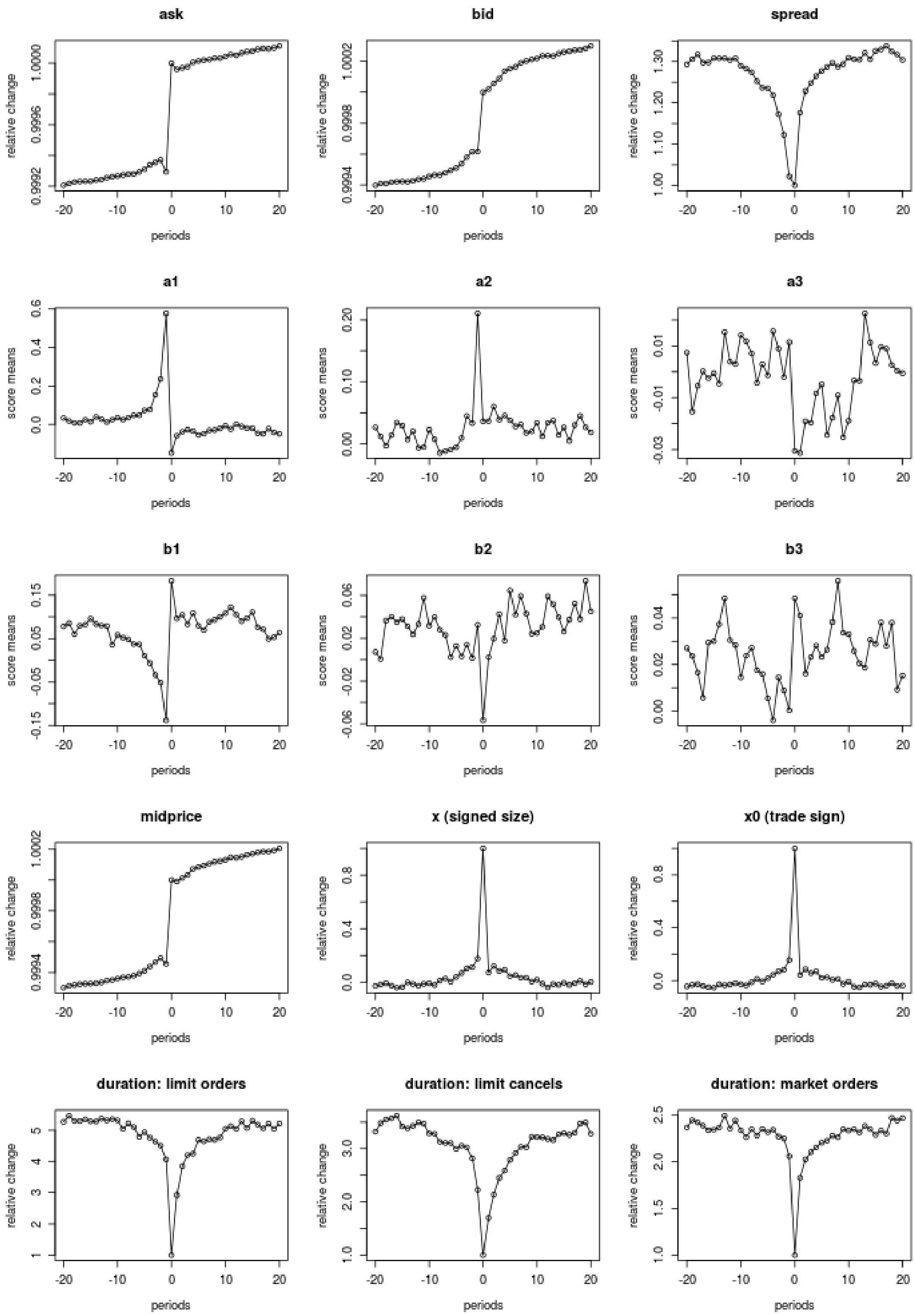


Impulse-response functions:aggressive market orders. Ticker: MOL

8.7 Figure 7

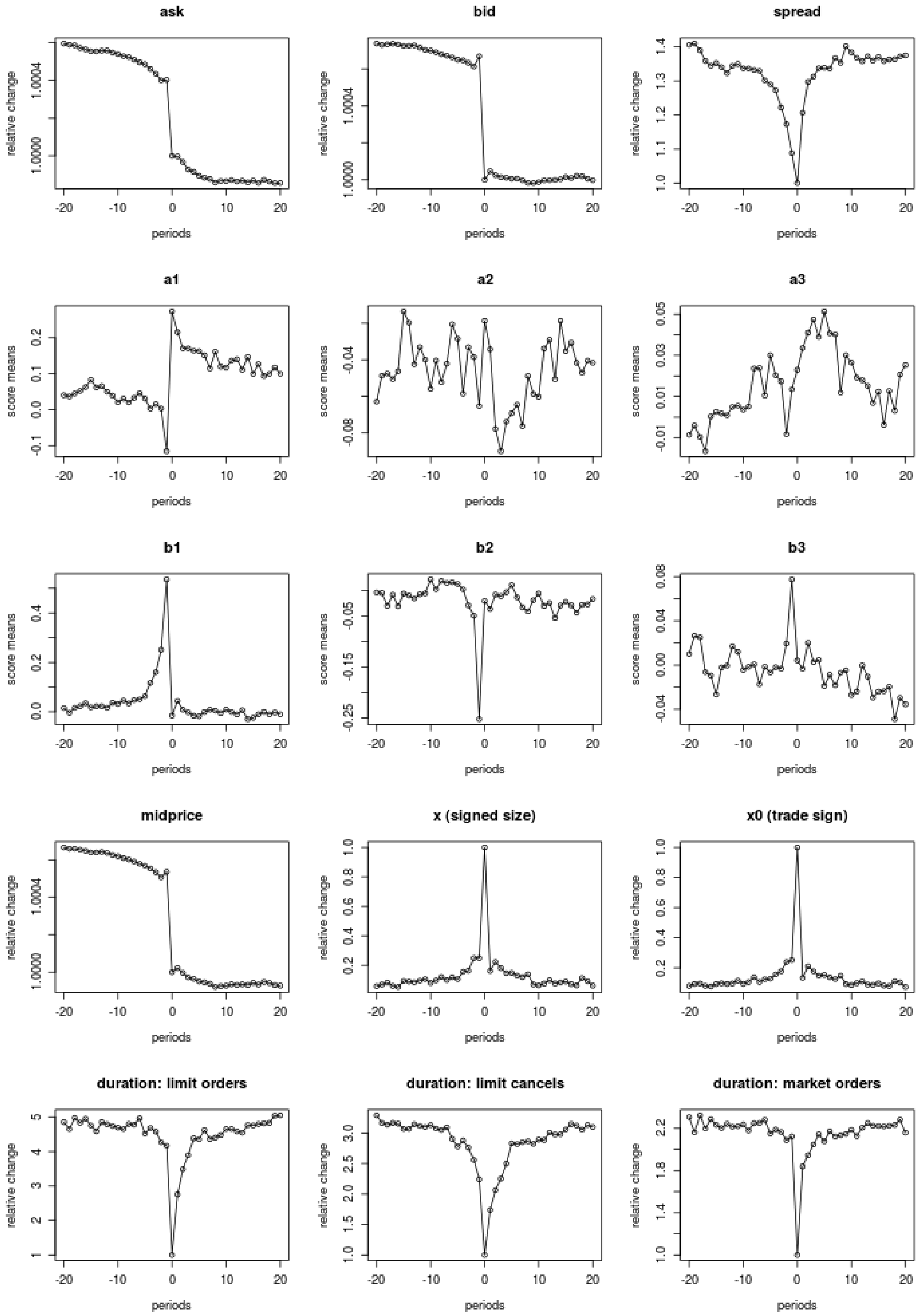
Note: The figure shows the means of the variables for 20 periods before and 20 periods after the aggressive buys. Ticker: OTP.

Figure 7: Robustness, Event study for aggressive market orders



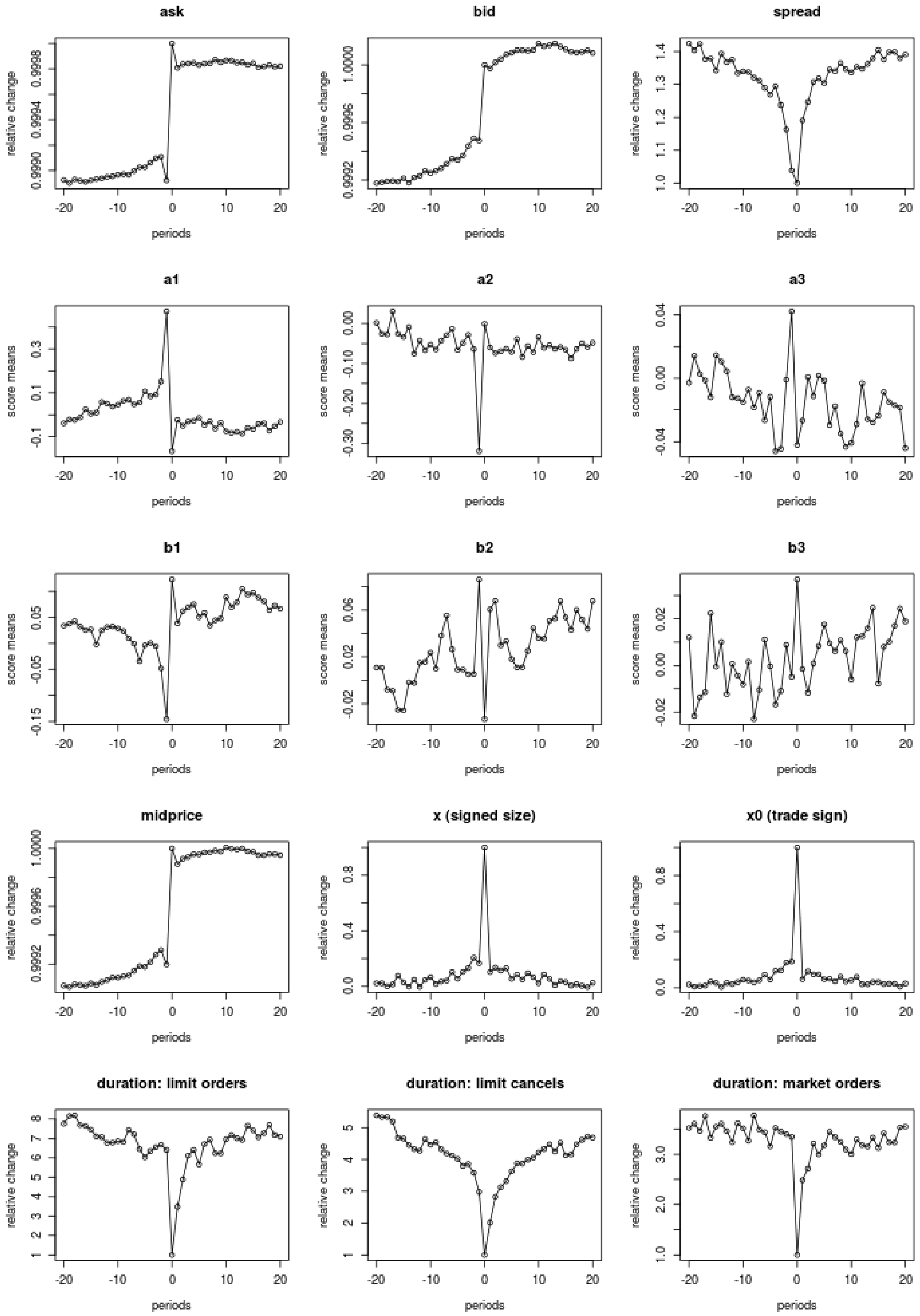
Robustness, Event study for aggressive market buy. Ticker: OTP

Note: The figure shows the means of the variables for 20 periods before and 20 periods after the aggressive sells. Ticker: OTP.



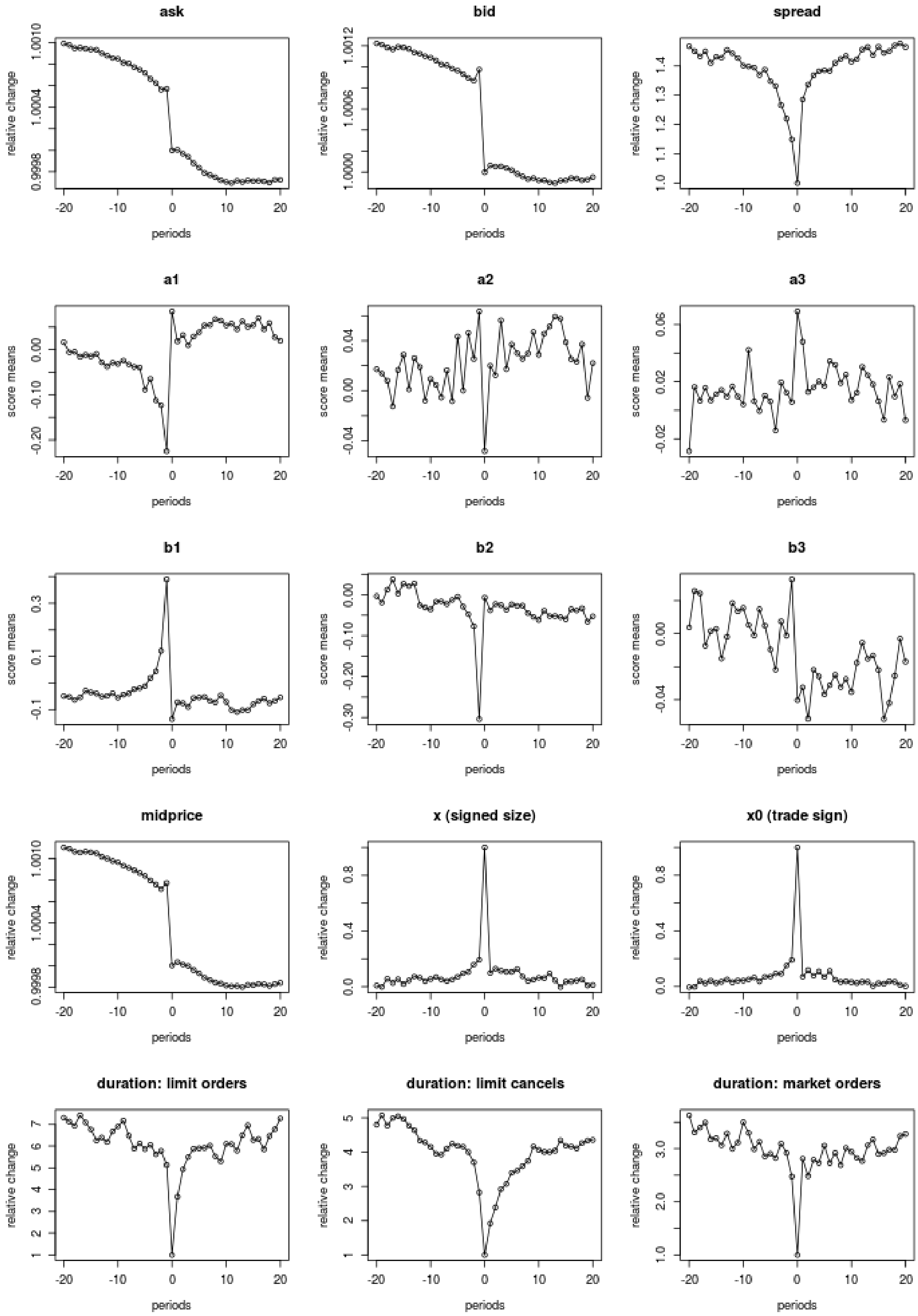
Robustness, Event study for aggressive market sell. Ticker: OTP

Note: The figure shows the means of the variables for 20 periods before and 20 periods after the aggressive buys. Ticker: MOL.



Robustness, Event study for aggressive market buy. Ticker: MOL

Note: The figure shows the means of the variables for 20 periods before and 20 periods after the aggressive sells. Ticker: MOL.



Robustness, Event study for aggressive market sell. Ticker: MOL