Forthcoming in Quantitative Finance

The Dynamics of Ex-ante Weighted Spread: An Empirical Analysis*

4 November 2019

Georges Dionne[a,b] Xiaozhou Zhou[a,c,†]

[a]Canada Research Chair in Risk Management, HEC Montréal, Montréal H3T 2A7, Canada

[b]Finance Department, HEC Montréal, Montréal H3T 2A7, Canada

[c]Faculty of Management (ESG), University of Quebec at Montreal, H3C 3P8, Canada

Abstract

We model the evolution of the ex-ante weighted spread (EWS) embedded in an open Limit Order Book (LOB) and investigate the impact of observed market-related variables on the spread. Our modeling involves decomposing the joint distribution of the weighted spread into simple and interpretable distributions. Our main results have several implications: (i) EWS features high persistence in autocorrelation; (ii) lower-level LOB remains liquid even after a high trade imbalance; (iii) lower- and higher-level LOB react to temporal spread change and trade imbalance in different ways; and (iv) both trade durations and quote durations have seasonality effects. We also show, through a simple high frequency trading exercise, that the use of the model can be economically important. Further, our model provides an estimation of market resilience.

Keywords: Limit order book, Ex-ante weighted spread, Decomposition model, Liquidity, Resilience.

JEL classification: C22 C41 C53 G11

1 Introduction

Since its introduction into financial markets, Limit Order Book (LOB) has received considerable attention from academicians, practitioners, and regulators. The state of the LOB reflects two fundamental elements in finance: liquidity and information. The shape of the LOB is a concrete

*We thank Yann Bilodeau for his help in constructing the dataset and comments. We also thank Tolga Cenesizoglu, Thierry Foucault, Christian Gourieroux, Gabriel Yergeau, the editor, two anonymous referees, and participants at the 2016 Portsmouth- Fordham Financial conference, 2017 China Meeting of the Econometric Society and the 27th Asian FA Annual Meeting for their remarks. This work was supported by the Social Sciences and Humanities Research Council in Canada [435-2012-1503]; the Canada Foundation for Innovation [219145]; and the Fonds de Recherche sur la société et la culture de Québec [149001].

†Corresponding author at: Faculty of Management (ESG), University of Quebec at Montreal (UQAM), 315 rue Sainte-Catherine Est Montreal, Quebec, Canada, H2X 3X2. Tel.: +1 514 987 3000 ext 0999. E-mail addresses: georges.dionne@hec.ca (G. Dionne), zhou.xiaozhou@uqam.ca (X. Zhou).

form of forward-looking liquidity for traders who seek immediacy. As noted by Amihud and Mendelson (1986), illiquidity can be measured by the cost of immediate execution. In a traditional dealer market, each stock has one designated liquidity provider whose quoting strategy is not disclosed to investors ex-ante. In this context, the cost of immediate execution can only be ex-post deduced from the transactions. However, the extensive use of electronic limit order markets by a large number of exchanges grants investors access to information about ex-ante liquidity, which is determined by price schedules and the corresponding available volumes in the LOB (Glosten (1994), Jain (2005)). As a result, the cost of immediate execution is (partially) visible[1] and measurable before transactions. Recent studies related to ex-ante liquidity include Irvine et al. (2000), Coppejans et al. (2004), Domowitz et al. (2005), Giot and Grammig (2006), Beltran-Lopez et al. (2009), and Beltran-Lopez et al. (2011). According to Aitken and Comerton-Forde (2003), ex-post liquidity measures involve trade-based measures, while ex-ante liquidity measures are order-based. The former measures are the most widely used and indicate what the traders have obtained in the realized transaction. The second group captures the cost related to potential immediate trading.

The shape of the LOB is also an outcome of limit orders from both informed and uninformed traders. Earlier theoretical models assume that the LOB is solely constructed by limit orders submitted by uninformed traders and that market orders contain information.[2] Consequently, the shape of the LOB is determined by uninformed liquidity providers who have to protect themselves from traders with superior information. However, recent theoretical models (Parlour (1998), Foucault et al. (2005), Goettler et al. (2009)) allow informed traders to submit both market orders and limit orders, and conclude that informed traders do use limit orders in their strategy design. As a result, the state of the LOB can better predict future price. The existence of this prediction power is analyzed by a large number of empirical studies (Cao et al. (2008), Kalay and Wohl (2009), Pascual and Veredas (2010), Cenesizoglu et al. (2018), among others). In general, they argue that state of the LOB, which is characterized by variables such as depth, slope, convexity and imbalance, has prediction power on either short-term price movement or volatility.

Given the importance of the LOB in price formation and in gauging liquidity and information asymmetry, the questions of how the LOB evolves and what determines the dynamics of

[1] Because most exchanges allow also iceberg and hidden orders. In addition, due to the latency, the realized cost at execution could be different from the expected cost based on the information of the LOB before submitting market orders. We thank an anonymous referee for pointing out the importance of latency.

[2] See Kyle (1985), Glosten and Milgrom (1985), and Glosten (1994).

the LOB are important but still open. To fill this gap, this paper focuses on the dynamics of the ex-ante weighted spread (EWS). Typically, this weighted spread is a measure of the state of the LOB. Compared with the widely used best bid-ask spread, ex-ante weighted spread provides a more complete picture of the shape of the LOB and captures more information embedded in it. Theoretical models attempt to explain the shape of the LOB with various sources. One class of theoretical models takes information asymmetry as the determinant of the shape of the LOB (Rock (1990), Glosten (1994), Goettler et al. (2005), and Goettler et al. (2009)). In another category of theoretical models with the absence of asymmetric information, nonexecution probability, waiting costs (traders' patience), as well as competition among traders are determinant factors of the shape of the LOB (Foucault (1999), Foucault et al. (2005), and Rosu (2009)). Moreover, the shape of the LOB is also highly affected by high-frequency trading (HFT) strategies. As shown by Hendershott and Riordan (2013), for stocks of DAX30, high-frequency traders represent 52% of market order volume and 64% of nonmarketable limit order volume. Hagstromer and Norden (2013) examine data from NASDAQ-OMX Stockholm and find that market makers constitute the lion's share of HFT trading volume (65%-71%). Other factors that probably influence the shape of the LOB are particular setups of trading mechanism and regulatory issues. Riordan and Storkenmaier (2012) examine the effect of a technological upgrade on the market liquidity of 98 actively traded German stocks, and show that both effective spreads and average price impacts drop with the upgrade. Brogaard et al. (2015) find that liquidity improves for the overall market after introduction of colocation services.

Instead of theoretically identifying the determinants of the shape of the LOB, this paper attempts to empirically capture a more general and realistic LOB evolution pattern that is much more complete than that characterized by structural models. Specifically, this study models the ex-ante weighted spread (EWS) using a tractable decomposition model that allows for various factors in a flexible way, and tests several empirical implications stemming from theoretical models. Furthermore, we attempt to quantify the effect of market-related high frequency variables on these factors. To do so, we construct and model the ex-ante weighted spread to capture the dynamics of the lower-level and higher-level LOB. Having found that our model can capture the dynamics of EWS effectively, we then show, through a simple high frequency trading exercise for all stocks from our sample, that the use of the model can also lead to economic gains. Finally, our model allows for practitioners to get an estimation of resiliency. Market resiliency is an important dynamic phenomenon that has received little attention in empirical studies. Market conditions with large spreads are less liquid and less resilient (Foucault et al. (2005)). Having a good measure of the ex-ante weighted spread can be instrumental to estimate market resiliency and obtain a good predictor of trading aggressivity.

To our knowledge, we are the first to consider modeling the ex-ante weighted spread using a decomposition model and including a large set of factors. Given the particularity of UHF data and the complexity of microstructure analysis, one possible modeling framework involves consistently decomposing the joint distribution of a target variable into simple and interpretable distributions. The idea of decomposition was pioneered by Rogers and Zane (1998), and aims at constructing observation-driven models in the sense of Cox et al. (1981). The decomposition model was first used to analyze transaction price dynamics. Hausman et al. (1992) and Russell and Engle (2005) propose an Autoregressive Conditional Multinomial (ACM) and ordered Probit model respectively. Rydberg and Shephard (2003) achieve the same goals by decomposing the joint distribution of tick-by-tick transaction price changes into three sequential components. And the decomposition model permits to predict price movements or price level with the help of simulations. McCulloch and Tsay (2001) model the transaction price variation process using the decomposition model. In their framework, they initialize a price variation and duration (PCD) model that decomposes the price variations into four factors, and introduce time and liquidity dimensions in modeling price variation dynamics. The duration between two consecutive transactions and the number of trades during this duration are modeled as implicit factors for the price changes. In total, they use six conditional models to capture the dynamics of price changes. Manganelli (2005) applies the decomposition methodology when investigating the simultaneous interaction between duration, volume and return. Two subgroups, classified by trade intensity, perform different dynamics. The decomposition framework remains flexible for more complicated modeling. Depending on different modeling assumptions, addition or deletion of certain factors is possible.

Our paper differs from the literature in several respects. First, instead of aggregating the time for a fixed interval, our analysis contains a time dimension. Specifically, our paper models the dynamics of tick-by-tick liquidity, and takes trade and quote durations as a proxy of trading activities, and investigates their roles in explaining the dynamics of open LOB. It is widely known that one important feature of the order-driven market involves the use of high-speed computers and advanced algorithms. As a result, the trading frequency shrinks from the time frame of minutes to the time scale of microseconds (even nanoseconds in some exchanges). By modeling data at tick-by-tick frequency, we attempt to take into account all available trading and quoting information. It is widely recognized that trade can convey private information and have an impact on the quote. Hasbrouck (1991) shows that, in an order-driven market, the price impact of trades is positive, and large trades cause the spread to widen. Intuitively, when facing informed traders, market makers protect themselves by quickly widening the spread and closely monitoring market order arrivals. Recently, the studies of Baruch et al. (2017) and Brogaard et al. (2019) show that limit orders play an important role in price discovery regardless of the existence of trading. Therefore, both trade duration and quote duration could be relevant measures for information flow or market dynamics. In addition, regarding model implementation, once the model is estimated on tick-by-tick frequency, we can test the model performance and compute EWS by Monte Carlo simulation for any horizon without re-estimating the model.

Second, by applying a decomposition model, we perform a much finer analysis of ex-ante weighted spread and take advantage of econometric modeling by attempting to capture a more general and realistic LOB trading pattern that is much more complete than that characterized by structural models. Specifically, following Engle and Lunde (2003) and Rydberg and Shephard (2003), we use different factors to model the dynamics of weighted spread changes.[3] Our main objective is to answer the question of how information sets of limit order traders are updated after trading and quoting activities by identifying the possible determinants of each factor from a set of market-related variables. Our empirical findings not only test several empirical implications derived from theoretical models but also offer guidance for new theoretical models in market microstructure. Practically, our modeling is also greatly useful for the Smart Order Routing (SOR) system[4] or for large financial institutions that participate in the market as real-time market makers.

Third, regarding the explanatory variables, in addition to the lagged dependent variables, we also include various market-related variables in the different factor equations. Whereas most papers take one variable as the explanatory variable and suppose that this variable can summarize all the trade information, our variables are volume-related, duration-related and trade imbalance related. Among these variables, we also distinguish between the short-run and long-run[5] variables to reflect their time dimension. Our results provide several conlusions: First, to model the dynamics of EWS, it is essential to include the lagged auto-dependent structure to capture

[3]The factors used to model the dynamics of the EWT include trade duration, quote duration, activity, direction, and size factors.

[4]Smart Order Router is a system designed to submit orders in the best available way by relying on the market condition and defined rules. Usually, SOR searches for the best execution price across fragmented markets. In this paper, we use SOR to refer to the execution practice that has the same objective as a general SOR but is applied to the temporal dimension (over the course of the trading day).

[5]Short-run variables are variables at a given time point, whereas long-run variables summarize the information over an interval.

the high persistence of autocorrelation; Second, most market-related variables have significant impacts on the dynamics of EWS; Third, lower- and higher-level LOB react to temporal spread change and trade imbalance in different ways; Fourth, the trade durations and quote durations have an obvious seasonality pattern, whereas the seasonality pattern for other factors is much weaker.

The rest of the paper is organized as follows: Section 2 describes the Xetra trading system and the ex-ante weighted spread modeled in this study. Section 3 presents the decomposition model and the market-related variables used to explain the dynamics of each factor. Section 4 applies our econometric model and reports the results of estimation, and in-sample and out-of-sample tests. Section 5 shows, through a simple high-frequency trading exercise, that the information captured by our model is also economically important. Section 6 provides an application of our decomposition model to resilience estimation. Section 7 concludes the paper and proposes new research directions.

2 Xetra Trading System and Ex-ante Weighted Spread

2.1 Xetra Trading System

Electronic trading systems have been adopted by many stock exchanges during the last two decades. The data used in this study are from the Xetra trading system, which is operated by Deutsche Börse at the Frankfurt Stock Exchange (FSE) and has a similar structure to the Integrated Single Book of NASDAQ and Super Dot of NYSE. The Xetra trading system realizes more than 95% of the total transactions at German exchanges. In this study, we focus on continuous trading.

During continuous trading,[6] there are no dedicated market makers and all liquidity comes from limit orders in the LOB. The Xetra trading system imposes a Price-Visibility-Time Priority condition, where the electronic trading system places the incoming order after checking the price and timestamps of all available limit orders in the LOB. Our database includes 20 levels of LOB information,[7] which means that, by monitoring the LOB, any registered member can

[6] There are two types of trading mechanisms during normal trading hours: call auction and continuous auction. A call auction can be organized once or several times during the trading day in which the clearance price is determined by the state of the LOB and remains as the open price for the following continuous auction.

[7] Fully hidden orders and the hidden part of an iceberg order are not observable in our dataset. However, as we observe the state of the LOB before and after the transaction, we can evaluate if a market order hits hidden orders or not. Our backtest results show that fewer than 3% of the market orders run into hidden orders, which represents about 6% of trade volumes. The presence of hidden orders makes our EWS slightly underestimating the actual liquidity. We thank one anonymous referee for pointing out the impact of hidden orders on the EWS.

evaluate the liquidity supply dynamics and potential price impact of a market order. However, there is no information on the identities of market participants. A more detailed description of the reconstruction of the LOB is available in the online appendix.

2.2 Ex-ante Weighted Spread

Ex-ante weighted spread is an instantaneous round-trip *relative* price impact for a given trade size. In this study, we define the ex-ante weighted spread as follows:

$$EWS^q = \frac{P^q_{net,buy} - P^q_{net,sell}}{P_{mid}} \times 10000\,, \tag{1}$$

$$P^q_{net,buy} = \frac{\sum_{k=1}^{K-1} P_{k,i} \cdot v_{k,i} + P_{K,i} \cdot v_{K,i}}{v} \quad \text{and} \quad v_{K,i} = v - \sum_{k=1}^{K-1} v_{k,i}\,,$$

where q is the potential size in Euros,[8] $P^q_{net,buy}$ is the average price when a buy market order of q Euros arrives and $P^q_{net,sell}$ relates to the average price for a sell market order of q Euros. v is the total volume bought by a market order of q Euros. $P_{k,i}$ and $v_{k,i}$ are the kth level ask price and volume available, respectively. $v_{K,i}$ is the quantity left after $K-1$ levels are completely consumed by the market order of q Euros. $P^q_{net,sell}$ is computed in a similar way. P_{mid} is the mid-quote of the bid-ask spread. Intuitively, it is also the cost in basis points of an immediate demand for liquidity from buy and sell market orders. For example, an EWS of 10 basis points related to a market order of 25,000 Euros means that the cost (or spread) caused by, simultaneously, buying and selling a market order of 25,000 Euros is 25 Euros. By choosing a different volume q, we can identify the EWS on the open LOB as shown in Figure 1. For comparison purposes, we adjust q to reflect the lower-level and higher-level LOB for each stock.[9] The previous market microstructure literature that considers the quantity available in LOB includes Irvine et al. (2000), Domowitz et al. (2005), and Coppejans et al. (2004), among others.

The EWS is based on P_{mid} and the difference between $P^q_{net,buy}$ and $P^q_{net,sell}$. Theoretically, there are infinite combinations of $P^q_{net,buy}$ and $P^q_{net,sell}$ for the same difference. That is, the spread

[8] To avoid the impact of stock price and outstanding shares across different stocks, for each stock, we choose q from its own trade volume distribution.

[9] Given that q is ad-hoc, hereafter, we use the notations EWS^{Low} and EWS^{High} for low-level spread and high-level spread, respectively. In addition, we keep EWS^q as a general term for ex-ante weighted spread.

may come from either side or both sides of the LOB. However, our study focuses on stocks' global spread. For both buy-side and sell-side, the corresponding one-side EWS can be defined and computed in a similar fashion. Figure 2 presents the average EWS as a function of q for 30 stocks in DAX30 for May 2011.

[Insert Figure 1 here]

[Insert Figure 2 here]

The EWS closely relates to Kyle's (1985) liquidity criteria: tightness, depth, and resilience. Specifically, the EWS is a measurement of the instantaneous depth-dependent tightness. Compared with the widely used bid-ask spread, the EWS is a more sensible measure because it considers both price and volume. Further, our model captures the evolution of the EWS, which corresponds to resilience. Practically, the EWS also can be used for several ends: first, it can help decision making in security selection when constructing a portfolio. Among the stocks with the same correlation with the market portfolio, a small EWS stock will decrease the trading cost and ultimately provide a higher net return. Second, the EWS can also be used for comparison purposes. For instance, a cross-listing stock may have different liquidity features in different markets. By using the EWS, one can quantify this difference by choosing a given volume.

3 Methodology

3.1 Model

To better capture the dynamics of EWS, we first include a time dimension that provides information on trading intensity. Following Engle and Lunde (2003), we consider trade and quote as a bivariate point process. Based on the timestamps of these point processes, we can define two types of duration: trade duration and quote duration, which constitute a bivariate duration process. However, due to the non-synchronization problem shown in Figure 3, we further assume that the trade times are the initiators for both the following trade and the next quote update.[10] Consequently, trade durations and quote durations with the same index share the same original timestamp[11]. The economic intuition behind the assumption is that the limit order traders in

[10] Lu and Abergel (2018) show that trades are more likely to be the driving force of the trade-quote and LOB dynamics.

[11] We also estimate the model by supposing that the quote updates initiate the dynamics. The results remain similar.

open LOB update their quotes by observing transactions. After each transaction, we compute the quote duration based on the very last transaction.

[Insert Figure 3 here]

As mentioned by Engle and Lunde (2003), by taking the transaction times as the origin of each pair of durations, two possible situations may occur for quote duration: an uncensored observation or a censored observation. The uncensored duration is when the quote update occurs before the next trade arrival and the censored duration happens when the following trade arrives before the quote update. We denote x_i and y_i as the trade duration and quote duration, respectively, and further define the observed quote duration $\tilde{y_i} = (1 - d_i) \cdot y_i + d_i x_i$, where $d_i = I_{\{y_i > x_i\}}$.

Apart from the time dimension, we use the above-mentioned EWS as the measure for the state of the LOB. In the uncensored situation, we take the average of the measure within the first quote update timestamp and the following trade timestamp. Its evolution can be written as:

$$EWS_i^q = EWS_0^q + \sum_{k=1}^{i} Z_k \, , \tag{2}$$

where Z_k is defined as the kth rounded signed change in EWS^q. In our dataset, Z_k is stationary and the stationarity is tested by the augmented Dickey–Fuller test.[12]

We define p as the joint density for trade duration, quote duration and EWS^q changes. We propose the following decomposition for this joint density of the kth mark:

$p(x_k, \tilde{y_k}, z_k^q \mid F_{k-1}; \omega)$

$= g(x_k \mid F_{k-1}; \omega_1) \cdot f^{Dur}(\tilde{y_k} \mid x_k, F_{k-1}; \omega_2) \cdot f^A(A_k \mid x_k, \tilde{y_k}, F_{k-1}; \omega_3) \cdot$

$f^D(D_k \mid x_k, \tilde{y_k}, A_k, F_{k-1}; \omega_4) \cdot f^S(S_k \mid x_k, \tilde{y_k}, A_k, D_k, F_{k-1}; \omega_5) \, .$

We define x_k and $\tilde{y_k}$ as duration factors, which relate to the trade duration and observed quote duration, for Z_k. Conditional on information set F_{k-1} and two durations, A_k takes the value of 0 or 1, which indicates if there is a change in the kth EWS^q. Conditional on $A_k = 1$, D_k relates to the direction of the EWS^q change by taking on the value -1 and $+1$. Finally, given the information set (F_{k-1}, $A_k = 1$, D_k), S_k takes on positive integers and indicates the size of the change. ω relates to the parameter set including $\omega_1, \omega_2, \omega_3, \omega_4$, and ω_5, which are the parameters for factors of trade duration, observed quote duration, activity, direction and size.

[12] The augmented Dickey-Fuller test rejects the hypothesis of a unit root for Z_k for all stocks in our sample. For the sake of brevity, we do not present our test results here. They are available from authors.

The motivation for our choice of factors is as follows. A tractable decomposition model allows for simple, observable, flexible, and interpretable factors. We decompose the Z_k into the activity, direction, and size factors because they capture different facets of a single change in EWS^q. The first factor, activity, measures if EWS^q will change or not after a trade. The second factor, direction, provides information on increase or decrease in the following EWS^q if there is a change. Finally, the factor of size assesses the magnitude of this change. Further, as shown below, we choose the auto-logistic model for the activity and direction factors, and the geometric model for the size factor because these models are concave, and numerical optimization can be done easily and reliably.

3.2 Models for Temporal Factors

We adopt the Log-ACD model originally introduced by Bauwens and Giot (2000) in modeling the irregularly spaced trade durations, which represents a main characteristic of high frequency data:

$$\frac{\mathrm{x_k}}{\psi_{\mathrm{k}}} = \varepsilon_{\mathrm{k}}, \tag{3}$$

$$\psi_k = \exp\left(\omega + \sum_{j=1}^{p} \alpha_j \varepsilon_{k-j} + \sum_{j=1}^{l} \beta_j \ln \psi_{k-j} + \Psi' W_{k-1}\right), \tag{4}$$

where $\psi_k = E(x_k | F_{k-1})$ and ε_k is a i.i.d. random variable following the generalized gamma distribution with unit expectation. The process of duration is composed of a sequence of de-seasonalized durations. W_{k-1} is a vector of market-related variables available at $k-1$, which includes market-related variables and quote-related variables. We use the Log-ACD because it is more flexible in modeling, and the positivity constraint on durations is always respected.[13]

We adopt a similar structure for observed quote duration, that is

$$\frac{\tilde{\mathrm{y_k}}}{\phi_{\mathrm{k}}} = \epsilon_{\mathrm{k}}, \tag{5}$$

$$\phi_k = \exp\left(\mu + \sum_{j=1}^{p} \rho_j \epsilon_{k-j} + \rho_{j+1} \epsilon_{k-1} d_{k-1} + \sum_{j=1}^{l} \delta_j \ln \phi_{k-j} + \Phi' V_{k-1}\right), \tag{6}$$

[13]The ACD (Autoregression Conditional Duration) model is proposed by Engle and Russell (1998); it is widely used for duration modeling.

where $\phi_k = E(\tilde{y_k} \,|F_{k-1})$, ϵ_k is supposed to be i.i.d exponential distributed and the error distribution is supported by the estimation convergence. In the equation, we add a term with a censored dummy variable to capture the impact of censored observation and the vector of market-related variables V_{k-1}, which may have some common variables with W_{k-1}. We show in the following section that because quote durations are conditional on transactions, one possible determinant variable could be the expected trade duration available at tick k.

3.3 Models for the Activity, Direction, and Size Factors

We next turn to explain the modeling for the activity, direction, and size factors. In our dataset, these three factors are all stationary, which is confirmed by the augmented Dickey–Fuller test.[14] The dynamics of each stationary factor are modeled by an autoregressive structure and market condition variables. We include the autoregressive part because Z_k and all three factors feature a high persistence in autocorrelation. More specifically, we adopt a structure called the GLARMA (Generalized Linear Autoregressive Moving Average) binary model, which is a generalized structure of auto-logistic structure allowing for moving average-type behavior (Shephard (1995)). The use of market condition variables is straightforward in that liquidity is determined or driven by market conditions.

Activity is a bivariate variable that takes the values of 0 or 1 to indicate whether there is a change in the EWS^q. To this end, we use the auto-logistic model (Cox et al., (1981)). Given that the log-likelihood function of the auto-logistic model is concave, numerical optimization can be done easily and reliably. However, the high-frequency data often exhibit a slow decay for longer lags in an autoregressive structure. Thus there is a trade-off between bias and variance, i.e., inference with too few parameters may be biased, while that with too many parameters may cause precision and identification problems. To solve this, the auto-logistic model for activity is defined as:

$$f\,(A_k = 1\,|F_{k-1},\, x_k,\, \tilde{y_k}\,) = p(\theta_k^A), \text{where } \; p(\theta_k^A) = \frac{\exp(\theta_k^A)}{1+\exp(\theta_k^A)} \tag{7}$$

$$\text{and } \theta_k^A = \Pi_A^{'} M_{k-1}^A + g_k^A, \quad g_k^A = \sum_{j=1}^{p} \gamma_j^A g_{k-j}^A + \sum_{j=1}^{l} \lambda_j^A A_{k-j}\,.$$

[14]The augmented Dickey-Fuller test rejects the hypothesis of a unit root for the activity, direction, and size factors for all stocks in our sample. For the sake of brevity, we do not present our test results. But they are available from authors.

$$\text{Consequently, } f(A_k = 0\,|F_{k-1},\, x_k,\, \tilde{y_k}\,) = \frac{1}{1+\exp(\theta_k^A)},$$

where M_{k-1}^A is the vector of market-related variables for the activity factor known at $k-1$. In this logistic modeling, the parameter θ_k^A is time-varying and depends on both its own lag variables, such as lags of g_k and A_k, and some market-related variables. The model will be first validated by applying the Ljung-Box test on the standardized errors defined by:

$$u_k^A = \frac{A_k - p(\theta_k^A)}{\sqrt{p(\theta_k^A)(1-p(\theta_k^A))}}\,, \tag{8}$$

which should be uncorrelated with zero mean and unit variance. Moreover, we evaluate the model's performance by using the McFadden's pseudo-R squared, the Receiver operating characteristic (ROC) and Count accuranry.[15]

In a similar way, the direction factor, conditional on the activity factor, is specified by another binary process on $+1$ or -1 ($+1$ means that spread becomes larger, and -1 is related to a smaller spread for trading volume q) and is estimated by another auto-logistic model:

$$f\,(D_k = 1\,|F_{k-1},\, x_k,\, \tilde{y_k},\, A_k = 1\,) = p(\theta_k^D), \text{ where } \; p(\theta_k^D) = \frac{\exp(\theta_k^D)}{1+\exp(\theta_k^D)} \tag{9}$$

$$\text{and } \theta_k^D = \Pi_D' M_{k-1}^D + g_k^D, \quad g_k^D = \sum_{j=1}^{p} \gamma_j^D g_{k-j}^D + \sum_{j=1}^{l} \lambda_j^D D_{k-j}\,,$$

$$\text{Consequently, } f(D_k = -1\,|F_{k-1},\, x_k,\, \tilde{y_k},\, A_k = 1\,) = \frac{1}{1+\exp(\theta_k^D)}\,.$$

M_k^D is a vector including market-related variables of subset F_{k-1} and Π^D is a parameter vector. Note that the vectors M^D and M^A might have some identical market-related variables.

Once the model is estimated, we use the Ljung-Box test to validate its ability to capture the main features of the data. The test will be applied to standardized residuals:

$$u_k^D = \frac{D_k - (2p(\theta_k^D) - 1)}{2\sqrt{p(\theta_k^D)(1-p(\theta_k^D))}}\,. \tag{10}$$

The model is also validated by the McFadden's pseudo-R squared, the Receiver Operating Characteristic (ROC) and Count accuracy.

[15]The McFadden's R squared measure is defined as $R^2_{McFaden} = 1 - \frac{log(L_c)}{log(L_{null})}$ where L_c denotes the likelihood value from the current fitted model and L_{null} denotes the corresponding value for the null model. ROC evaluates binary model accuracy at various threshold settings (Swets 1986, 1988)) by considering Type I and Type II errors. Count accuracy measures the in-sample accuracy predicted by the model.

The last factor is Size, which captures the magnitude of Z_k. We adopt a geometric process for the size factor because of its simplicity and generality:

$$S_k\,|(F_{k-1},\,x_k,\,\tilde{y_k},\,A_k=1)\sim 1+\mathrm{g}(\lambda_k)\;, \tag{11}$$

$$\lambda_k=\frac{\exp(\theta_k^{Siz})}{1+\exp(\theta_k^{Siz})},$$

$$\theta_k^{Siz}=\Pi_{Siz}^{'}M_{k-1}^{Siz}+g_k^{Siz}\;\text{and}\;\;g_k^{Siz}=\sum_{j=1}^{p}\gamma_j^{Siz}g_{k-j}^{Siz}+\sum_{j=1}^{l}\lambda_j^{Siz}S_{k-j}\,,$$

where M_{k-1}^{Siz} is a vector of market-related variables and Π_{Siz} is the corresponding parameter vector. $g(\lambda_k)$ indicates the geometric distribution with parameter λ_k.[16] In order to capture the asymmetry between up-move size and down-move size, we add a direction variable in the vector of market-related variables. In equation (11), we add 1 to the geometric distribution because the minimum change is 1. We also apply the Ljung-Box statistics to standardized residuals to evaluate the model. Given the conditional distribution of Size, we have

$$E(S_k-1\,|F_{k-1},\,x_k,\,\tilde{y_k},\,A_k=1)\,)=\frac{1-\lambda_k}{\lambda_k}\,, \tag{12}$$

$$Var(S_k-1\,|F_{k-1},\,x_k,\,\tilde{y_k},\,A_k=1)\,)=\frac{1-\lambda_k}{(\lambda_k)^2}. \tag{13}$$

Standardized residuals are computed as

$$u_k^{Siz}=\frac{S_k-1-E(S_k-1\,|F_{k-1},\,x_k,\,\tilde{y_k},\,A_k=1)}{\sqrt{Var(S_k-1\,|F_{k-1},\,x_k,\,\tilde{y_k},\,A_k=1)}}\,, \tag{14}$$

and an adequate modeling requires that u_k^{Siz} be uncorrelated with zero mean and unit variance. To summarize, for the estimation process, we can estimate each factor separately by using the Maximum Likelihood approach. The BIC criteria will be applied for the model selection, especially for the choice of number of lags. Moreover, to make sure that the model captures the main features of the data, we perform various tests to evaluate the performance of the models. Then, with the previous specifications, all the observations can be classified into one of the three following categories:

1) There is no change in the EWS, that is, activity factor $A_k=0$ and no direction and size factors.

[16] The general probability distribution function is $f(x=m)=\lambda(1-\lambda)^m, 0<\lambda<1, m=0,1,2,...$

2) Weighted spread increases and the size changes by at least one unit. The corresponding factors are: $A_k = 1$, $D_k = 1$, and $S_k = s_k$;

3) Weighted spread decreases and the size changes by at least one unit. The corresponding factors are: $A_k = 1$, $D_k = -1$, and $S_k = s_k$;

The maximum likelihood estimation function is equal to:

$$L(\omega_1, \omega_2, \omega_3, \omega_4, \omega_5; x_k, \tilde{y_k}, z_k^q)$$

$$= \sum_{k=1}^{n} \begin{bmatrix} \log[g(x_k \mid F_{k-1}; \omega_1)] + \log[f^{Dur}(\tilde{y_k} \mid x_k, F_{k-1}; \omega_2)] \\ \\ +I_k(1) \cdot K1 + I_k(2) \cdot K2 + I_k(3) \cdot K3 \end{bmatrix}, \tag{15}$$

where

$K1 = \log(f^A(A_k \mid F_{k-1}; \omega_3))$;

$K2 = \log(1 - f^A(A_k \mid F_{k-1}; \omega_3)) + \log(f^D(D_k \mid F_{k-1}; \omega_4)) + \log(f^S(S_k \mid F_{k-1}; \omega_5))$;

$K3 = \log(1 - f^A(A_k \mid F_{k-1}; \omega_3)) + \log(1 - f^D(D_k \mid F_{k-1}; \omega_4)) + \log(f^S(S_k \mid F_{k-1}; \omega_5))$.

$I_k(1)$, $I_k(2)$, $I_k(3)$ correspond to the indicator function related to the three categories mentioned above.

In sum, the advantage of this modeling is that the partition enables us to simplify the modeling and computation task by specifying the suitable econometric models for the marginal densities of trade duration and conditional densities for quote duration, along with factors such as Activity, Direction and Size. In addition, for different purposes, the model could also be extended to a more or less complicated context by including other factors. In these decomposition models, one of the crucial tasks is to identify the market-related variables.

3.4 Market-related Variables Set

Given the model defined above, we need to identify the possible market-related variables, apart from the own lags of each component. In this study, we attempt to find variables with economic interpretation. In the literature, the most widely used variables have been spread, trading volume and price (see, for example, Hasbrouck (1996), Goodhart and O'Hara (1997), Coughenour and Shastri (1999) and Madhavan (2000)). The intuition is that trading activities and LOB trader behavior are related. For instance, in a volatile trading period, trading volume increases and trade duration and quote duration decrease. Consequently, these variations generate a volatile open LOB.

The first market-related variable is relative spread change, which is computed by the following formula:

$RelativeSpread_k = 100 \cdot (ln(ask_k) - ln(bid_k))$.

Its variation is measured by:

$DeltaSpread_k = RelativeSpread_k - RelativeSpread_{k-1}$,

where ask and bid are the best sell price and best buy price available in open LOB. The advantage of relative spread is that it is dimensionless and can be used to directly compare different stocks. Given that the relative spread captures quasi-instantaneous information and might be noisy, another spread-related variable is the average relative spread over the ten most recent observations:

$AveSpread_k = \frac{1}{10} \sum_{i=1}^{10} RelativeSpread_{k-i}$.

Regarding the volume dimension, the first market-related variable is the square root of the volume (number of shares), $SquareRoot\,(vol)$, that initiates the current trade. There are two reasons for the use of square root, one is to weigh down the large trade volume, and the second is that the price impact proves to be a concave function of market order size (Hasbrouck (1991)). If the volume that initiates the current trade is large, we expect a volatile situation and, consequently, the trade duration and quote duration are likely to be short.

The second volume-related variable should capture the imbalance of the signed trade. To this end, we adopt the depth measure proposed by Engle and Lange (2001), which is defined as follows:

$Abs(sign.vol)_k = \mid \sum_{i=1}^{10} sign_{k-i} volume_{k-i} \mid$,

where the $sign_{k-i}$ and $volume_{k-i}$ are the trade sign and trade volume for the $(k-i)th$ trade. The trades are classified into buy-initiated and sell-initiated according to the rule of Lee and Ready (1991). Intuitively, when the depth measure increases, it indicates that the trades are imbalanced and the market is dominated by one-sided pressure.

The third dimension is duration. We define two sorts of duration, back-quote duration and quote-quote duration, which are different from trade duration and quote duration. The former is used to consider the duration between the first update of the LOB after the previous trade and the following trade, which contains quote information. Note that the back-quote duration could be zero due to the fact that the quote duration might be censored when the trade occurs before the update of open LOB. The way in which the data are sampled ignores some quotes when there is more than one update between two trades. This might not be a concern when

75% of the quotes are preserved, as in Engle and Lunde (2003). However, in a market where the open LOB is more active, as in the Xetra trading system, ignoring the quote activity may be a concern. In fact, only about 20% of the quotes are preserved in our dataset.

The quote-quote duration variable considers the duration for which there is no change in the EWS. As a result, it will be used only in explaining the components such as direction and size when the measure changes.

The above variables will be all (or partially) included in the market-related variable vectors for different components. In addition, we put time-of-day dummy variables in the models of the three factors to remove seasonality, a stylized fact in high-frequency data.

Table 1 presents the summary statistics of durations and market-related variables for May 2011. The number of monthly trade observations across all stocks ranges from 43,567 to 234,826. The trade frequency is also confirmed by the corresponding average trade durations. That is, stocks with larger numbers of trades correspond to shorter trade durations. Regarding the average trade volumes, there are big differences: they vary from 180 to 1,669 Euros, meaning that the selected stocks have different trading volume patterns. The average quote durations are relatively small, and there is evidence that the dynamics in the open LOB are more active than those of trades. Considering other market-related variables, the averages of $DeltaSpread$ and ΔEWS are naturally close to zero. $AveSpread$ is dimensionless, so we can consider this variable as an indicator of the transaction costs for small volumes. The mean of $AveSpread$, for all stocks, is around 0.05%, meaning that the average remains relatively stable across the stocks. The average trade imbalance variable $Abs(sign.vol)$ varies from 767 to 20,726.9 Euros, indicating the existence of different trading patterns across the stocks.

[Insert Table 1 here]

4 Estimation and Results on the EWS

Our dataset covers three months: July 2010, May 2011 and June 2011. For the sake of brevity, we present and compare the estimation results for ΔEWS^{Low} and ΔEWS^{High} for May 2011.[17] We estimate our model for the 30 stocks of the DAX using the first two-week data and do the out-of-sample test with the data of the third week. For each stock, EWS^{Low} and EWS^{High}

[17] Results for the two other months are similar and available from the authors.

represent ex-ante weighted spread based on the 20th and 80th percentiles of its own historical trading volume distribution.

4.1 Temporal Factors

The estimation results of deseasonalized trade and quote durations are presented in Table A.2 and Table A.4 of the appendix. Both tables show the estimated parameters for lagged auto-dependent and market-related variables. A more detailed analysis can be found in the online appendix.

4.1.1 Trade Duration Factor

In the modeling, the lagged auto-dependent variables are used to capture the degree of persistence in the trade durations. The market-related variables will capture the effect of different variables on trade durations.

The overall results on trade durations, presented in Table A.2, are stable across stocks over the three sample periods and provide new empirical evidence about trade duration dynamics. First, the sums of the coefficients for the auto-dependent part is around 0.9, suggesting that trade durations are highly persistent. Second, the coefficients for $DeltaSpread$ and $AveSpread$ are positive and significant for 30 and 25 stocks respectively, indicating that when liquidity decreases, traders slow down their trading intensities. Moreover, the coefficient for the short-term variable $SquareRoot\,(vol)$ is negative and significant for all stocks, indicating that large trades increase trading intensity. However, the coefficient for the long-term variable $Abs(sign.vol)$ is positive and significant for 20 stocks. This means that, when the trade imbalance increases, trading activity slows down or keeps the same speed.

We validate our duration model by the Ljung-Box statistics. The results at different lags for the resulting standardized residuals are presented in Table A.3. Compared with the Ljung-Box statistics on trade durations (Table A.1), our results present evidence that the lagged auto-dependent part is capable of removing this autocorrelation feature in the trade durations because the Ljung-Box statistics have been reduced dramatically and, for most stocks, the hypothesis of no autocorrelation cannot be rejected.

4.1.2 Quote Duration Factor

Similar to the trade duration equation, we include lagged auto-dependent structure and market-related variables as explanatory variables for the quote duration equation. We include more market-related variables in the quote duration equation than in the trade duration equation because we assume that the trade durations are market-related and can explain the quote duration dynamics. More specifically, the market-related variables we use to explain the dynamics of quote durations are: trade-duration-related variables, censored effect variable, DeltaSpread, AveSpread, SquareRoot(vol) and Abs(sign.vol). Table A.4 presents the corresponding estimate results.

The effect of market-related variables on the quote duration can be briefly summarized as follows: first, $AveSpread$ and $SquareRoot\,(vol)$ have a negative impact on quote durations. This suggests that when the average spread is large and the trading volume is high, LOB traders speed up their revisions. Second, the coefficient for the trade imbalance variable $Abs(sign.vol)$ is significantly negative for the 30 stocks, suggesting that liquidity providers rapidly react to this imbalance.

Comparing the Ljung-Box statistics on residuals from the quote duration model in Table A.5 with those of raw quote durations in Table A.1, we find that the statistics have been largely reduced and, for most stocks, the hypothesis of no autocorrelation cannot be rejected.

4.2 Activity Factor

Up to now, we have analyzed the dynamics of trade durations and quote durations. Conditional on the these temporal variables, we can further analyze other dimensions of weighted spread. As mentioned above, we decompose the change in the weighted spread into three components: Activity, Direction and Size. Similar to the time dimension, we also include lagged auto-dependent variables, market-related and time dummy variables in each factor modeling. The M^A vector includes expected trade duration, expected quote duration, $DeltaSpread$, $AveSpread$, $SquareRoot\,(vol)$, $Abs(sign.vol)$, $BackQuote\ duration$, and $\triangle EWS$. We also include time dummy variables to control intraday seasonality.

Table 2 and Table A.7 report the estimated results of the weighted spread activity factor for EWS^{High} and EWS^{Low}, respectively. The activity process is a binary process in which the value 1 means a change in the EWS. To capture the high persistence of autocorrelation in the activity factor, we adopt the GLARMA structure introduced by Rydberg and Shephard (2003). We also include market-related variables. As shown in Table 2, for all stocks, the coefficients of the "GLAR" part are positive and significant with a mean of 0.88, which suggests high persistence in autocorrelation for the activity factor. More specifically, there is a cluster effect in activity: the change in the EWS is more likely to be followed by another change.

[Insert Table 2 here]

We are also interested in the effect of market-related variables on the dynamics of liquidity. For the time dimension variables, expected trade duration and expected quote duration do not have the same effect on the probability of EWS change. In particular, for the activity factor of EWS^{High}, a longer expected trade duration increases the probability of EWS change significantly for 14 stocks, whereas a longer quote duration significantly decreases this probability for 29 stocks. The same effect of quote duration is found for the activity factor of EWS^{Low}, and expected trade duration seems to have more impact on the activity factor of EWS^{Low}. In the tick-by-tick trading framework, as Dionne et al. (2009) and Dionne et al. (2015) demonstrate, a longer trade duration has a positive impact on price volatility. As a result, a longer trade duration increases the probability of EWS change. However, quote duration measures the quote intensity. A longer quote duration means a less active open LOB. Therefore, the quote is likely to be unchanged.

Regarding spread-related variables, $AveSpread$ has a positive effect on the probability of EWS change for activity factor of EWS^{High} for all stocks, and the impact of $DeltaSpread$ on the activity factor is negative. Because $AveSpread$ measures relative long-term liquidity and $DeltaSpread$ captures the dynamics of short-term liquidity, the estimation results suggest that the higher-level of the LOB reacts more to relative long-term than short-term liquidity. When long-term liquidity decreases (higher $AveSpread$), LOB traders are more prudent, and are more likely to update their quotes. Therefore, the probability of a EWS^{High} change increases. Regarding the lower-level of the LOB, we find that the activity factor reacts both to $DeltaSpread$ and $AveSpread$. Note that the activity factor only tells us whether the EWS changes or not; there is no information on the direction and magnitude of change.

Regarding volume-related variables, $SquareRoot\,(vol)$ and $Abs(sign.vol)$ affect the probability of EWS^{High} change in different ways. The coefficients of $SquareRoot\ (vol)$ are significantly positive for both EWS^{Low} and EWS^{High} changes. This means that short-term large trades are likely to increase the probability of EWS changes. As mentioned above, large trades are likely to be informative. Under this circumstance, LOB traders are more likely to review their quotes and then the resulting LOB changes. The effect of $Abs(sign.vol)$ is not significant for the activity factor of EWS^{High} and significantly negative for that of EWS^{Low}. This is not intuitive when we consider the trade imbalance as a measure of information asymmetry. One explanation is that algorithm traders stay at the lower-level of the LOB and provide liquidity by keeping a stable spread.

Another time dimension variable, *BackQuote duration*, also has a positive impact on the probability of weighted spread change. This is in line with the estimated results for trade duration. The effect of expected trade duration is higher than that of expected quote duration. Therefore, a longer *BackQuote duration* implies a more volatile market and the LOB is likely to be updated. For EWS^{Low} and EWS^{High}, as expected, the coefficient is positive and significant at the 1% level for all stocks. This means that when a stock is less liquid or has more adverse selection risk, there is a greater chance that LOB traders will review their quote. The state of the LOB then changes. Concerning the time dummy variables (not presented), we find that there is a week seasonality pattern only for some stocks in certain time intervals; most of the periods do not exhibit a seasonality pattern.

We validate the activity factor modeling by several in-sample tests presented in Table 3. The Ljung-Box statistics at different levels on the standardized residuals shows that the GLARMA part can capture this autocorrelation feature very well because all statistics have been reduced to the level of the critical values. Other in-sample tests presented in the same table includes the McFadden's pseudo-R squared, the Receiver Operating Characteristic (ROC) and Count accuracy. The average McFadden's pseudo-R squared is 23.93%, average ROC is 0.612 and the count accuracy is 60.87%.

[Insert Table 3 here]

4.3 Direction Factor

Direction is also a binary process: the value 1 means an increase in the EWS and -1 means a decrease in the EWS. Conditional on the activity factor, the direction factor gives more information about the change in the EWS. Table 4 presents the estimation results of the direction factor for the GLARMA structure and other market-related variables. Specifically, the sums of the "GLAR" part are around 0.6, suggesting a cluster effect, and the "MA" part is around -1.5, indicating a mean-reverting feature. In other words, the decrease in the EWS is likely to be followed by an increase in the EWS, and vice versa.

[Insert Table 4 here]

The market-related variables in the direction equation are: *QuoteQuote duration, DeltaSpread, AveSpread, SquareRoot (vol), Abs(sign.vol), BackQuote duration* and $\triangle EWS$. *QuoteQuote duration* is defined as the duration between two EWS changes. Given that the direction component is observed only when the activity factor is equal to one, it is more reasonable to use a temporal variable to capture this time interval. For the direction factor of EWS^{Low}, we find that 26 stocks have a significant and negative coefficient for *QuoteQuote duration*. It appears that liquidity is likely to increase after a longer no-change period. However, the results for EWS^{High} shows that the higher-level of the LOB is less likely to be affected by the quoting intensity.

Considering the spread-related variables, a larger *DeltaSpread* is likely to cause a decrease in liquidity. Intuitively, when the spread increases, this means that LOB traders keep away from mid-quotes, so the EWS is likely to increase. The same results are found for the direction factor of ΔEWS^{Low}. Compared with *DeltaSpread*, the *AveSpread* has the opposite effect on the direction factor. This suggests that the permanent increase in the spread is likely to lead to an increase in liquidity. It seems evident that when the traders have to pay a higher liquidity premium, the LOB traders (i.e, liquidity providers) are willing to provide liquidity by reducing the spread.

Regarding the volume-related variables, the coefficient of *SquareRoot* (*vol*) is positive for both ΔEWS^{High} and ΔEWS^{Low}, meaning that the current large trades are likely to lead to a higher EWS, which is consistent with the literature. Intuitively, a large trade is likely to generate a higher price impact. However, the trade imbalance variable *Abs*(*sign.vol*) has a negative and significant effect on the direction factor for EWS^{Low} and confirms that when there is a need for liquidity, the liquidity providers increase liquidity by reducing spread. However, the effect of *Abs*(*sign.vol*) on the direction factor of EWS^{High} is much less pronounced. Only half of the stocks have a significantly negative effect, implying that the higher-level of the LOB is less sensitive to liquidity demand.

For ΔEWS^{Low} and ΔEWS^{High}, an increase in EWS is likely to lead an increase in liquidity.

This increase provides evidence of mean-reverting in EWS dynamics. We also use dummy variables to capture seasonality in the direction factor. The estimated results (not presented) show that the coefficients are not significant, meaning that there is no clear seasonality effect on the direction factor.

The in-sample test for the model of the direction factor are reported in Table 5 and Table A.10, respectively. The direction factor is highly autocorrelated and the hypothesis of no autocorrelation is rejected at all confidence levels for all stocks. However, the Ljung-Box statistics for the standardized residuals have been reduced significantly. We observe that the average McFadden's pseudo-R squared is 34.05%, the average ROC is 0.797 and the count accuracy is 73.21%.

[Insert Table 5 here]

4.4 Size Factor

The last factor is the size of the weighted spread change. Table 6 and Table A.11 report the estimated results for both ΔEWS^{High} and ΔEWS^{Low} . The sums of the "GLAR" part are around 0.71, suggesting a cluster effect in the size factor.

[Insert Table 6 here]

We include the same market-related variables as in the equation of the direction factor. *Quote-Quote duration* has a significantly postive effect on most of stocks with respect to both ΔEWS^{Low} and ΔEWS^{High}. Recall that *QuoteQuote duration* is the duration between two EWS changes. It indicates that liquidity is likely to increase slightly after a longer no-change period. The temporal variable *BackQuote duration* has a positive and significant effect on λ_k for both ΔEWS^{Low} and ΔEWS^{High}, indicating that even though the liquidity provider tries to incite the traders to trade by increasing the liquidity provision (our conclusion from the results of the direction equation), the magnitude of the liquidity increase (i.e., the EWS decreases) is moderate. However, if the trading intensity increases (i.e., the *BackQuote duration* decreases), liquidity is likely to decrease with a greater magnitude (i.e., EWS increases).

Regarding spread-related variables, a larger *DeltaSpread* is likely to cause a slight decrease in liquidity given that a higher *DeltaSpread* probably leads to a decrease in liquidity. Compared with *DeltaSpread*, *AveSpread* has the opposite effect on the size factor, which suggests that the permanent increase in the spread is likely to lead to a large increase in liquidity. It seems evident that when the traders have to pay a higher liquidity premium, LOB traders (i.e., liquidity providers) are willing to provide more liquidity by considerably reducing the spread. The coefficient of the $SquareRoot\,(vol)$ is negative for both ΔEWS^{High} and ΔEWS^{Low} meaning that the current large trades are likely to lead to a much higher EWS. However, the trade imbalance variable $Abs(sign.vol)$ has a significantly negative effect on the size factor for both ΔEWS^{High} (18 stocks) and ΔEWS^{Low}(15 stocks). One interpretation is that liquidity providers engage in aggressive spread reduction.

The last variable $\triangle EWS$ has a positive and significant effect on λ_k for both EWS^{Low} and EWS^{High} changes. This also suggests a slow resilience of the LOB. If the market is evaluated previously as less liquid based on EWS, the actual liquidity is prone to increase but the size of this increase is likely to be small.

We also attempt to capture seasonality by including time dummy variables in our model of size factor (not presented). Similar to the activity and direction factors, there is weak seasonality in the size component because most of the coefficients are not significant.

Table 7 reports the Ljung-Box statistics and adjusted R^2 of the size factor model.[18] Ljung-Box statistics have been significantly reduced after the introduction of the GLARMA structure. However, we should reject the hypothesis that the series of standardized residuals is not autocorrelated. Therefore, the model might have a specification problem on θ_k^{Siz} or a mild distributional failure. Note that θ_k^{Siz} can be specified in many different ways and the distribution for size factor can differ from the geometric distribution. The average adjusted R^2 is 29%.

[Insert Table 7 here]

4.5 Summary of Market Related Variables' Impact

We can compare the total effect of different market-related variables on changes in the Exante Weighted Spread (EWS). Table 8 summarizes the effect of key market-related variables on ΔEWS. For both lower-level and higher level of the LOB, higher $AveSpread$ predicts a lower EWS, suggesting mean-reversion dynamics in EWS. $SquareRoot\,(vol)$ has a significant positive effect on all the stocks and predicts a large increase in EWS, confirming a rapid reaction of the

[18]Because the size factor is not binary variable, we present the Ljung-Box statistics and adjusted R^2 to validate the model.

LOB to a large trade. Interestingly, the trade imbalance variable, $Abs(sign.vol)$, affects LOB differently: for the lower-level of the LOB, EWS^{Low} is more likely to remain the same after a higher trade imbalance; and for the higher-level LOB, the dynamic of EWS^{High} is less sensitive to $Abs(sign.vol)$. Finally, higher *DeltaSpread* is likely to lead a higher EWS for the lower-level of the LOB and have little impact on the higher-level of the LOB. Given these empirical results, we can conclude that 1) the LOB is constructed by active and sophisticated book traders, and they take positions in different levels of the LOB. 2) traders at the lower-level of the LOB are less worried about providing liquidity for a temporary liquidity shock proxied by order imbalance, and traders at the higher-level of the LOB are patient speculators who try to estimate the probability of large market order arrivals after a large transaction, as Rosu (2009) argued.

[Insert Table 8 here]

4.6 Out-of-sample Performance

Now, we turn our attention to the model's out-of-sample performance. Once the model is estimated, we follow Christoffersen (2003) and use Monte Carlo simulations to make multi-step forecasts and to test the model's performance. Parameters are estimated using data from the first two weeks of our sample, and the data from the third week are used to validate the model. Because the estimation is based on tick-by-tick frequency, one of the advantages is that one can compute the simulated liquidity for any interval without re-estimating the model. Given that the duration model is applied to deseasonalized duration, the simulated duration is not in calendar units. However, simulated duration and calendar time intervals are proportionally related. For instance, the same simulated interval relates to a shorter calendar time interval for a more liquid stock.

The simulations are realized as follows:

1. We generate the trading and quoting durations between two consecutive transactions and take them as input variables for other factors;
2. With the autoregressive structure, market condition variables and simulated durations in step 1), we obtain the corresponding activity, direction and size factors;
3. We repeat steps 1 and 2 for 5,000 paths.

To evaluate the model's performance, we first conduct a zero-mean t-test for the simulated series, and then compare the unconditional distribution of the simulated series $\check{Z}_k$ with that of the realized series, Z_k. Specifically, we compute the p-values for the one-sample zero mean t-test, the two-sample t-test and Pearson's Goodness-of-Fit test for each simulated series and take the average p-value. Table 9 presents the results of the corresponding statistical tests. It follows that 1) our model effectively captures the characteristics of unconditional distribution for higher-level changes, especially for the one-sample zero mean t-test and the two-sample t-test; 2) For lower-level changes, the model suffers a moderate loss of precision, suggesting some improvements could be gained from integrating more complicated distributions in our modeling.

[Insert Table 9 here]

In order to address the concern of how our model captures the temporal dimension of the real data, we also compare the sample autocorrelation function (ACF) of the simulated sample to that of the real data sample, and compute the mean squared error (MSE) of our simulated sample for various time horizons. We first compute the ACF for each simulated path of $\check{Z}_k$, and then take the average of the ACFs of the 5000 paths, and compare it with that of the real data. Table 10 reports the average simulated and empirical ACF from 1 to 5 lags. In general, we have negative ACFs for both simulated and empirical samples, which decrease as the lag increases. Also, the magnitude of our simulated ACFs is, on average, close to that of real data. Further, in Figure 4, we illustrate typical evolutions of Z_k for our representative stocks EOAN and MAN.[19] Lastly, we assess how the aggregated $\check{Z}_k$ from simulation deviates from real data by computing the aggregated $\check{Z}_k$ for various tick lengths and comparing them with the corresponding aggregated Z_k of the realized series. Table 11 shows the mean square error for various horizons of the 30 stocks. Our results show that our simulated data have small average errors for both short and long horizons.

[Insert Table 10 here]

[19]The variance of EWS_T^q is equal to $T \times \sigma_Z^2 \left(1 + 2\sum_{t=1}^{T-1} ACF(t) \times (1 - t/T)\right)$. It is a function of T and $ACF(t)$. In our simulations, EWS_T^q sometimes diverge gradually at large times even though Z_k is stationary with zero mean and our model captures well the autocorrelation of empirical data. The variance of EWS_T^q may become very large when the summation containing $ACF(t)$ does not efficiently cancel the effect of T. In practice, to avoid this blow-up at very large times, the aggregation of simulated Z_k should be done with a given number of ticks. This is how we proceed when showing the economic significance of our model in Section 5. We thank a referee for pointing out this issue.

[Insert Figure 4 here]

[Insert Table 11 here]

5 Economic Value of the Model

So far, our results provide statistically evidence in support of high persistence in autocorrelation and market condition variables. In this section, we show that the model we propose can also be economically significant. We do this by considering a simple stock liquidation scenario and comparing the trading costs between the uniform-order-submission strategy, the moving-average-submission strategy and the decomposition-model-based strategy. In real market, traders mainly have two sources of risk when liquidating a position: market risk and liquidity risk.[20] The order splitting practice can avoid the problem of price impact but extends order completion time, which makes market risk more pronounced, whereas large volume trades bear less market risk but have important price impacts. Given that our model focuses only on ex-ante liquidity (weighted spread), we set up the market environment as follows: 1) To ensure the same liquidation value for the three strategies, we require that the numbers of trades derived from the strategies are the same. In addition, for each trade, the volume is fixed. We choose the trade volume as the 20th percentile of historical trading volume distribution for each stock to have a small market impact; 2) all market-order submissions are in one-direction (buy only or sell only); 3) and, to have the minimum impact of market risk, we require model-based trades to follow the uniform trades closely. With these particular settings, our signals involve solely order submission time.
Specifically, the trading strategy we consider can be summarized as follows: we first simulate 5,000 paths only with the GLAR part of the model. For each path, we simulate the same number of ticks as in real data. We use the GLAR part only in order to create a fair estimation scenario that does not contain information on the future market condition. Then, we aggregate the tick-by-tick real and simulated series with a given number of ticks to form two samples. For each sample, we require our number of trades to equal 10% of total trades. The uniform strategy is applied directly to the real data sample and trade with a fixed frequency. For example, if we have 100 periods, the uniform strategy will trade 10 times at the 10th, 20th,..., and 100th time points,

[20] In this paper, market risk is related to uncertainty about stock mid-quote price, whereas liquidity risk is uncertainty about the shape of the LOB when liquidating the position.

respectively. The moving-average-submission strategy generates signals based on the comparison between the actual spread and its historical average.[21] More specifically, the moving-average-submission strategy trades when the actual spread is smaller than its historical average. This strategy continues until the required number of trades is obtained. For the 100-period scenario, we only trade the first ten times when the actual spread is smaller than its historical average. Finally, our model-based strategy uses multi-step forecasts derived from a simulated sample to generate trade signals. To see this, consider the same 100 periods. To generate the first trade signal, the model-based strategy compares the first ten simulated spreads and selects the period of the smallest one to send the first trade signal. Then, the model-based strategy repeats the same procedure for the second ten simulated spreads to generate the second trade signal. The model-based strategy ends up having the same number of trades (10) as the uniform and moving-average strategies. By following the signals from the three liquidation strategies, we compute and compare the total spread paid by these strategies. The difference is the cost savings from the more effective strategy.

Table 12 compares the performance of these three strategies for aggregations of various ticks. The decomposition-model-based strategy significantly outperforms the uniform order-submission strategy for all aggregations. For example, for the period of 10-tick aggregation, without taking into account other trading costs such as fixed operation fee and expenses related to model implementation, the average cost savings from paying less spread is about 16.17%. The economic gains decrease when competing with the moving-average-submission strategy. Based on the one-sample t-test which examines whether the model-based strategy dominates the uniform or moving average strategies, we conclude that on average, for aggregations of 30, 40, and 50 ticks, the decomposition-model-based strategy can always significantly generate cost savings. However, this cost-saving efficiency becomes less significant for aggregations of 10 and 20 ticks.[22]

[Insert Table 12 here]

6 An Estimation of Resilience

Another possible application of our model is to provide an estimation of market resilience based

[21] In this typical exercice, we use a moving window of 10 periods to calculate historical average.

[22] Consistent with many model forecasting studies, the results confirm that a simple moving-average strategy could be hard to beat when using real data.

on estimated parameters. Resilience is difficult to observe and estimate in real time given that after one liquidity shock, there are often other transactions before liquidity reverts to its initial level. The estimation of resilience can be thought of as the impulse response function derived from the Vector Autoregressive model. In the previous section, we modeled the dynamics of expected spread changes and examine the impact of several market-related variables on the changes. In a general sense, trades are translated into a long-run effect on mid-quote and short-run effect on spread. More specifically, the permanent price impact from trades will be reflected in a mid-quote increase or decrease over long periods. The spread around mid-quote, a proxy for liquidity, reverts to its initial state in the long-run if no other important liquidity shocks follow. This inherently dynamic feature of financial markets, well known as stock resilience, represents a vital dimension of market liquidity. There is time-based and probability-based resilience in the financial literature. Time-based resilience relates to the time required for the liquidity to revert to its initial state from a random, uninformative shock. In contrast, probability-based resilience refers to the probability that, after a liquidity shock, the spread reverts to its former level before the next transaction (Foucault et al. (2005)). In spite of its theoretical importance, stock resilience has received little attention in empirical research. With our decomposition model, we outline a framework based on Christoffersen (2012) and carry out a multi-step simulation experiment to deduce the time-based and probability-based resilience. In practice, our design allows practitioners to compare resiliency for different stocks and improve the efficiency of their optimal execution strategies.

As a simplified example, we suppose the following scenarios, (i) all market-related variables remain at their average levels, and (ii) there is an initial liquidity shock that is not followed by other significant liquidity shocks. The multi-step simulations are realized as follows:

1. We generate the duration between two consecutive transactions based on the estimated coefficients of the LogACD model;
2. With the simulated duration and estimated coefficients for the activity, direction and size factors, we generate Z_k for the $n+1$ periods ahead;[23]
3. Repeat steps 1 and 2 for 5,000 paths;
4. Calculate the average time (ticks) with which liquidity reverts to its initial state after a given liquidity shock.

[23] n is an arbitrary number of ticks and in our simulation, it takes the value of 1000.

5. Count the number of paths where the spread reverts to its initial state for any given tick.

For comparison purposes, we further compute the empirical time-based and probability-based resilience for real data. Specifically, we take the mode of tick-by-tick spreads as our reference spread, and select the moments when the current spread is higher than the reference spread as the moments for the occurrence of a liquidity shock. Then, we classify liquidity shocks according to their magnitude and calculate reversion time for all shocks with the same magnitude. Therefore, for each magnitude of shock, we have a sample reversion time. The sample average is the time-based resilience, and the value of the empirical cumulative distribution function evaluated at a given time is the corresponding probability-based resilience. Table 13 presents simulated and empirical time-based resilience for different magnitudes of shocks. In general, the reversion time increases with the magnitude of the shock. Specifically, the average of empirical reversion time ranges from 11.7 ticks to 40.7 ticks for 1 and 5 BPS shocks, respectively. The corresponding simulated time-based resiliences are 12.6 and 42.8, suggesting that our model produces comparable, but slightly longer, time-based resilience. Note that empirical resilience is also a noisy proxy of real resilience because other transactions often occur before liquidity reverts to its initial level. Table 14 reports probability-based resilience. The results are laid out similarly to those of time-based resilience. That is, the probability of recovery increases monotonically with the number of ticks and varies greatly across stocks. For one unit of liquidity shock, the empirical probability of recovery for a higher-level spread ranges from 49.79% on average at the 5th tick to 90.08% on average at the 30th tick. The corresponding simulated probability-based resilience is 48.98% and 73.76%. A similar pattern of resilience is found for the lower-level LOB and other periods in our sample.

[Insert Table 13 here]

[Insert Table 14 here]

7 Conclusion

Since the introduction of the open LOB trading mechanism, the state of open LOB has received considerable attention from academics, practitioners, and regulators because of its importance in price formation and in gauging liquidity and information asymmetry. This paper focuses on a measure of the state of the LOB: the ex-ante weighted spread (EWS). Different from an ex-post measure of liquidity and information asymmetry, the EWS is an ex-ante volume-dependent measure. The computation of the measure requires information such as the prices and the corresponding quantities available in the open LOB.

To model the dynamics of the EWS, we adopt the decomposition approach proposed by Rogers and Zane (1998). The EWS changes have been decomposed into five factors: trade durations, quote durations, activity, direction and size. To investigate the dynamics of each component, we apply the relevant econometric models to each factor and include the lagged auto-dependent structure and a wide range of market-related variables in the models. The models are validated by several in-sample tests and out-of-sample tests.

The main empirical findings are as follows: By including different microstructure-based variables, we first find that most market-related variables can influence the dynamics of both trade and quote durations.Moreover, the quote durations are influenced by the dynamics of trade durations, market-related variables and $\triangle EWS$. Second, to model durations and $\triangle EWS$, it is essential to include the lagged auto-dependent structure to capture the high persistence of autocorrelation. Third, most market-related variables have significant impacts on the dynamics of EWS. Fourth, the lower- and higher-level LOB react to temporal spread and trade imbalance in different ways. Fifth, trade durations and quote durations have an obvious seasonality pattern, whereas the seasonality pattern for other factors is much weaker.

Having found statistically significant evidence in support of high persistence in autocorrelation and market condition variables, we also show, through a simple high frequency trading exercise, that the use of the model can also be economically important. Finally, we demonstrate how to use our model to estimate resilience that is difficult to observe in real time.

Future research can take several avenues. Our study focuses on the impact of market-related variables on EWS changes. One alternative is to investigate how EWS change co-moves with trades. Another research direction is to decompose the EWS changes in a different order or into different factors to answer other microstructure questions such as the effect of news on resilience. However, the unsynchronization of the trade durations and quote durations between different stocks is a challenge, which might require a more complicated econometric model and reasonable assumptions of dependence.

References

Aitken, M., Comerton-Forde, C., 2003. How should liquidity be measured? Pacific-Basin Finance Journal 11, 45–59.

Amihud, Y., Mendelson, H., 1986. Asset pricing and the bid-ask spread. Journal of Financial Economics 17, 223 – 249.

Anatolyev, S., Shakin, D., 2007. Trade intensity in the russian stock market: dynamics, distribution and determinants. Applied Financial Economics 17, 87–104.

Baruch, S., Panayides, M., Venkataraman, K., 2017. Informed trading and price discovery before corporate events. Journal of Financial Economics 125, 561–588.

Bauwens, L., Giot, P., 2000. The logarithmic ACD model: an application to the bid-ask quote process of three NYSE stocks. Annals of Economics and Statistics / Annales d'Économie et de Statistique , 117–149.

Beltran-Lopez, H., Giot, P., Grammig, J., 2009. Commonalities in the order book. Financial Markets and Portfolio Management 23, 209–242.

Beltran-Lopez, H., Grammig, J., Menkveld, A.J., 2011. Limit order books and trade informativeness. The European Journal of Finance , 1–23.

Bilodeau, Y., 2013. Xetraparser [computer software]. HEC Montréal .

Brogaard, J., Hagstromer, B., Norden, L., Riordan, R., 2015. Trading fast and slow: colocation and liquidity. Review of Financial Studies 28, 3407–3443.

Brogaard, J., Hendershott, T., Riordan, R., 2019. Price discovery without trading: Evidence from limit orders. The Journal of Finance .

Cao, C., Hansch, O., Wang, X., 2008. Order placement strategies in a pure limit order book market. Journal of Financial Research 31, 113–140.

Cenesizoglu., T., Dionne., G., Zhou, X., 2018. Asymmetric effects of the limit order book on price dynamics. Working Paper, Canada Research Chair in Risk Management .

Christoffersen, P., 2012. Elements of financial risk management, 2rd edition. Academic Press .

Coppejans, M., Domowitz, I., Madhavan, A., 2004. Resiliency in an automated auction. Working paper, ITG Group .

Coughenour, J., Shastri, K., 1999. Symposium on market microstructure: a review of empirical research. Financial Review 34, 1–27.

Cox, D.R., Gudmundsson, G., Lindgren, G., Bondesson, L., Harsaae, E., Laake, P., Juselius, K., Lauritzen, S.L., 1981. Statistical analysis of time series: some recent developments. Scandinavian Journal of Statistics 8, 93–115.

Dionne, G., Duchesne, P., Pacurar, M., 2009. Intraday value at risk (IVaR) using tick-by-tick data with application to the Toronto Stock Exchange. Journal of Empirical Finance 16, 777–792.

Dionne, G., Pacurar, M., Zhou, X., 2015. Liquidity-adjusted intraday value at risk modeling and risk management: An application to data from Deutsche Borse. Journal of Banking & Finance 59, 202–219.

Domowitz, I., Hansch, O., Wang, X., 2005. Liquidity commonality and return co-movement. Journal of Financial Markets 8, 351–376.

Easley, D., O'Hara, M., 1987. Price, trade size, and information in securities markets. Journal of Financial Economics 19, 69–90.

Engle, R.F., Lange, J., 2001. Predicting VNET: a model of the dynamics of market depth. Journal of Financial Markets 4, 113–142.

Engle, R.F., Lunde, A., 2003. Trades and quotes: a bivariate point process. Journal of Financial Econometrics 1, 159–188.

Engle, R.F., Russell, J.R., 1998. Autoregressive conditional duration: a new model for irregularly spaced transaction data. Econometrica 66, 1127–1162.

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

Foucault, T., Kadan, O., Kandel, E., 2005. Limit order book as a market for liquidity. The Review of Financial Studies 18, 1171–1217.

Giot, P., Grammig, J., 2006. How large is liquidity risk in an automated auction market? Empirical Economics 30, 867–887.

Glosten, L.R., 1994. Is the electronic open limit order book inevitable? The Journal of Finance 49, 1127–1161.

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

Goettler, R., Parlour, C., Rajan, U., 2005. Equilibrium in a dynamic limit order market. The Journal of Finance 60, 2149–2192.

Goettler, R.L., Parlour, C.A., Rajan, U., 2009. Informed traders and limit order markets. Journal of Financial Economics 93, 67 – 87.

Goodhart, C.A.E., O'Hara, M., 1997. High frequency data in financial markets: Issues and applications. Journal of Empirical Finance 4, 73–114.

Hagstromer, B., Norden, L., 2013. The diversity of high-frequency traders. Journal of Financial Markets 16, 741 – 770.

Hasbrouck, J., 1991. Measuring the information content of stock trades. The Journal of Finance 46, 179–207.

Hasbrouck, J., 1996. Order characteristics and stock price evolution An application to program trading. Journal of Financial Economics 41, 129–149.

Hausman, J.A., Lo, A.W., MacKinlay, A.C., 1992. An ordered probit analysis of transaction stock prices. Journal of Financial Economics 31, 319–379.

Hendershott, T., Riordan, R., 2013. Algorithmic trading and the market for liquidity. Journal of Financial and Quantitative Analysis 48, 1001–1024.

Irvine, P.J., Benston, G.J., Kandel, E., 2000. Liquidity beyond the inside spread: measuring and using information in the limit order book. SSRN eLibrary .

Jain, P.K., 2005. Financial market design and the equity premium: electronic versus floor trading. The Journal of Finance 60, 2955–2985.

Kalay, A., Wohl, A., 2009. Detecting liquidity traders. The Journal of Financial and Quantitative Analysis 44, 29–54.

Kyle, A.S., 1985. Continuous auctions and insider trading. Econometrica 53, 1315–1335.

Lee, C.M.C., Ready, M.J., 1991. Inferring trade direction from intraday data. The Journal of Finance 46, 733–746.

Lu, X., Abergel, F., 2018. High-dimensional hawkes processes for limit order books: modelling, empirical analysis and numerical calibration. Quantitative Finance 18, 249–264.

Madhavan, A., 2000. Market microstructure: a survey. Journal of Financial Markets 3, 205–258.

Manganelli, S., 2005. Duration, volume and volatility impact of trades. Journal of Financial Markets 8, 377–399.

McCulloch, R.E., Tsay, R.S., 2001. Nonlinearity in high-frequency financial data and hierarchical models. Studies in Nonlinear Dynamics & Econometrics 5, 1–17.

Parlour, C., 1998. Price dynamics in limit order markets. Review of Financial Studies 11, 789.

Pascual, R., Veredas, D., 2010. Does the open limit order book matter in explaining informational volatility? Journal of Financial Econometrics 8, 57–87.

Riordan, R., Storkenmaier, A., 2012. Latency, liquidity and price discovery. Journal of Financial Markets 15, 416 – 437.

Rock, K., 1990. The specialist's order book and price anomalies. Working Paper,Harvard University .

Rogers, L.C.G., Zane, O., 1998. Designing and estimating models of high-frequency data. Unpublished paper .

Rosu, I., 2009. A dynamic model of the limit order book. The Review of Financial Studies 22, 4601–4641.

Russell, J., Engle, R., 2005. A discrete-state continuous-time model of financial transactions prices and times: the autoregressive conditional multinomial-autoregressive conditional duration model. Journal of Business & Economic Statistics 23, 166.

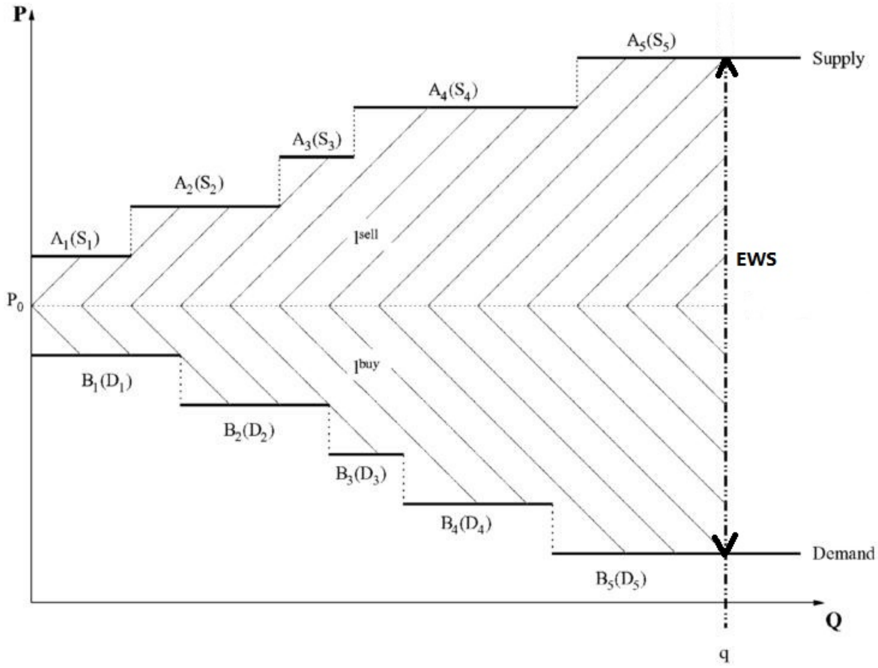
Rydberg, T.H., Shephard, N., 2003. Dynamics of trade-by-trade price movements: decomposition and models. Journal of Financial Econometrics 1, 2–25.

Shephard, N., 1995. Generalized linear autoregressions. Working paper, University of Oxford .

Swets, J.A., 1986. Indices of discrimination or diagnostic accuracy: Their rocs and implied models. Psychological Bulletin 99(1), 100–117.

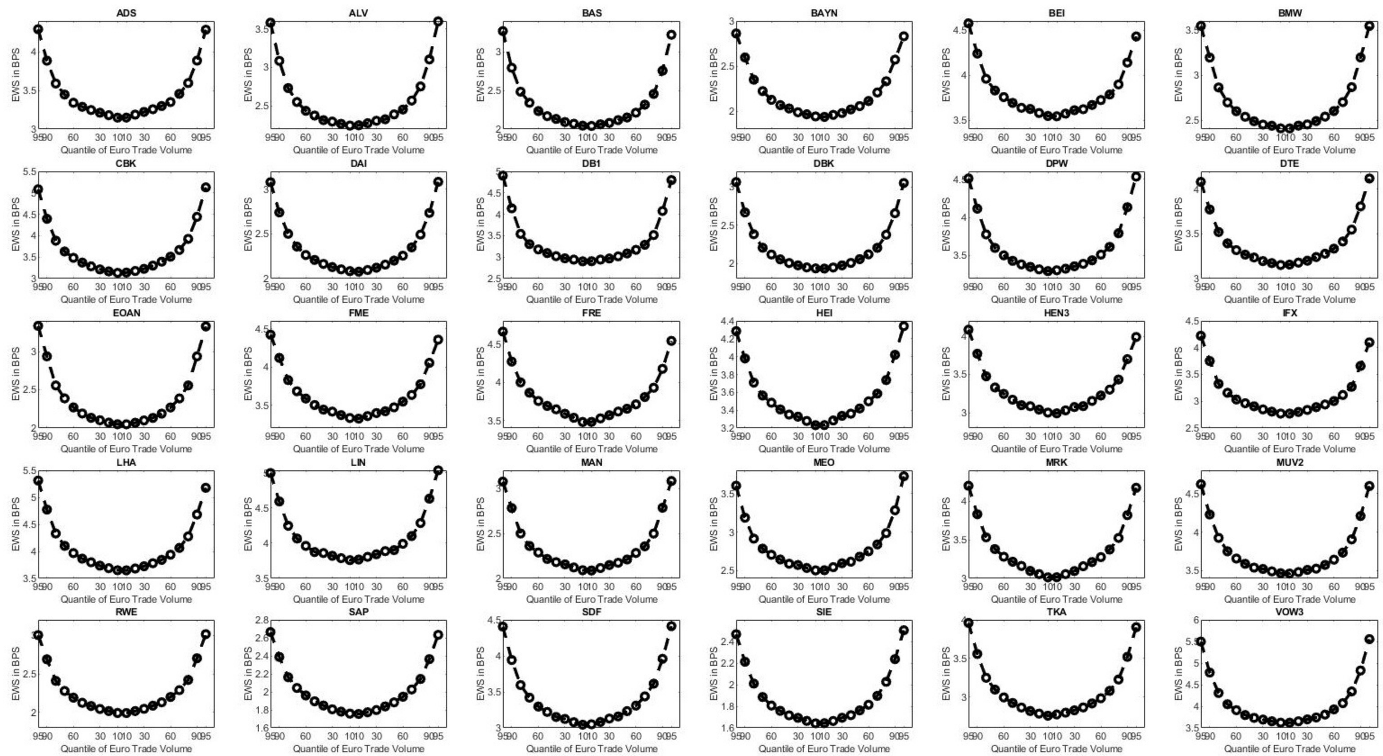
Swets, J.A., 1988. Measuring the accuracy of diagnostic systems. Science 240, 1285–1293.

Figure 1: Snapshot of Supply and Demand of Liquidity in the LOB



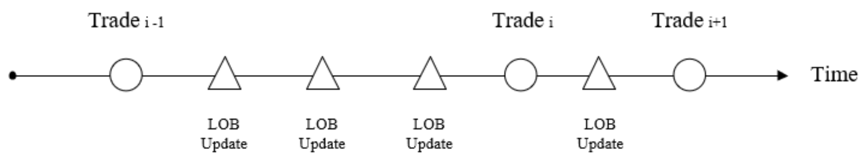
This figure presents a snapshot of the LOB and a relationship between EWS and a potential trade volume q. P_0 is the mid-quote price and $A_i(S_i)$ ($B_i(D_i)$) relates to Ask-side Supply (Bid-side Demand) at the level i.

Figure 2: Average EWS as a Function of Trading Volume in Euros



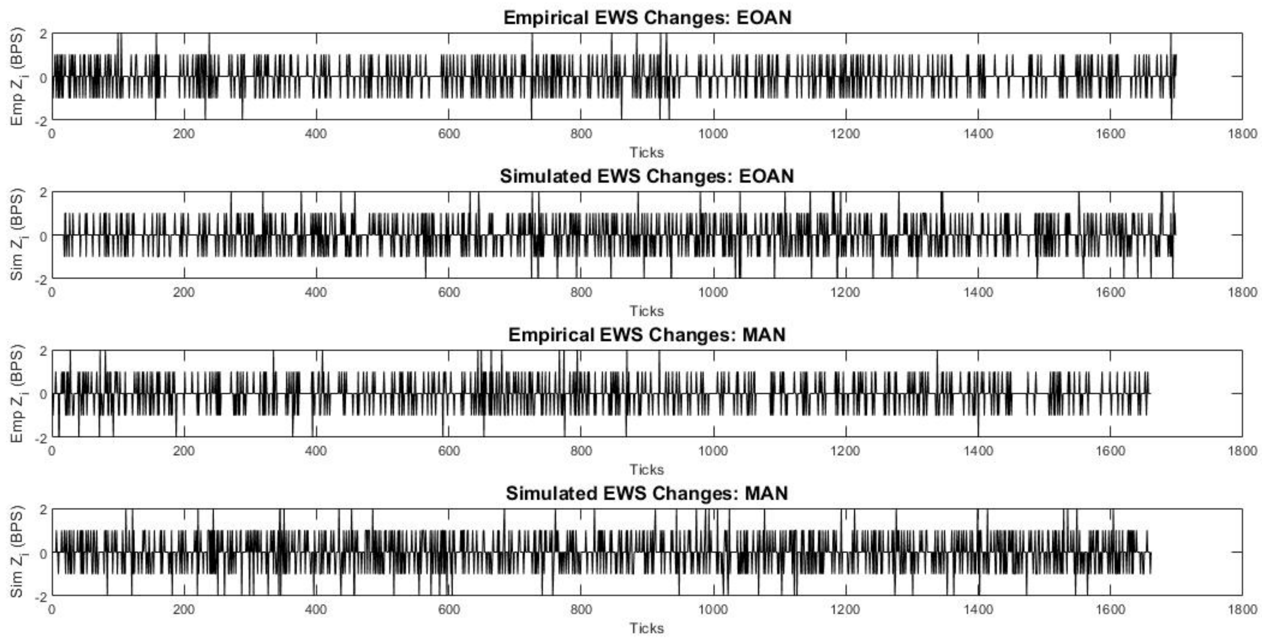
This figure presents the average EWS(q) as a function of trade volume q in Euros for both ask and bid sides for May 2011. q takes the percentile of 10, 20, 30, 40, 50, 60, 70, 80, 90, 95, 97 and 99 of the distribution of monthly tick-by-tick trade volumes.

Figure 3: Timestamps for Trades and Quote Update in Open LOB



This figure presents the temporal relation between trades and quote updates, which are represented by circles and triangles, respectively.

Figure 4: Evolution of Empirical and Simulated EWS



This figure presents empirical and simulated higher-level z_k of stocks of EOAN and MAN on the Monday of the third week of May 2011.

Table 1: Summary Statistics of Z_k^{low}, Z_k^{high} and Market-related Variables

Ticker	Company Name	Avg.Z^{Low}	Std.Z^{Low}	LB(15).Z^{Low}	Avg.Z^{High}	Std.Z^{High}	LB(15).Z^{High}	Avg.Price (Euros)	Avg.Volume (shares)	Avg.Trd.dur (seconds)	Avg.Qte.dur (seconds)	Avg.Delta Spread %	Avg.AvSpread %	Avg.Sign.vol (Euros)	Avg.Back.dur (seconds)	Nb_Obs
ADS	ADIDAS AG	-0.003	1.191	6422.54	-0.003	1.161	6027.59	51.754	13.934	8.926	0.091	3.98E-05	0.050	1407.08	6.428	74832
ALV	ALLIANZ SE	-0.001	0.841	17374.54	-0.001	0.841	15812.03	98.409	14.825	4.562	0.078	-1.71E-05	0.042	1871.88	3.525	146672
BAS	BASF SE	-0.001	0.859	17316.46	-0.001	0.834	16128.51	64.549	17.925	3.520	0.070	4.61E-05	0.035	2673.72	2.675	189907
BAYN	BAYER AG	-0.002	0.873	12164.57	-0.002	0.842	11148.08	57.428	17.181	5.903	0.072	4.90E-05	0.036	2164.32	4.582	113207
BEI	BEIERSDORF AG	-0.004	1.270	3122.24	-0.005	1.227	2713.05	45.116	12.933	15.301	0.058	1.06E-05	0.059	1154.22	10.837	43567
BMW	BAYER MOTOREN WERKE AG	-0.001	0.977	14167.34	-0.001	0.954	13172.27	61.847	15.343	4.334	0.056	-1.84E-05	0.041	1706.23	3.229	154370
CBK	COMMERZBANK	0.000	1.194	20946.28	-0.001	1.193	19152.88	3.620	49.725	2.850	0.146	1.00E-04	0.056	20726.86	2.055	234826
DAI	DAIMLER AG	-0.001	0.883	17786.77	-0.001	0.861	16495.25	49.730	18.117	3.974	0.056	2.91E-05	0.037	2387.94	3.047	168420
DB1	DEUTSCHE BOERSE AG	-0.003	1.176	7440.87	-0.003	1.137	6470.34	55.551	15.877	8.299	0.093	4.41E-05	0.045	2163.12	5.843	80512
DBK	DEUTSCHE BANK AG	0.000	0.857	19090.71	-0.001	0.841	17993.19	42.100	19.692	3.347	0.049	-3.43E-05	0.033	2968.92	2.524	199995
DPW	DEUTSCHE POST AG	-0.001	1.204	7302.23	-0.002	1.165	6563.85	13.462	29.764	9.819	0.172	5.88E-05	0.060	7182.48	7.549	68041
DTE	DEUTSCHE TELEKOM	-0.001	0.915	10198.27	-0.001	0.934	9160.87	10.753	41.963	7.483	0.226	1.07E-04	0.061	15823.93	5.880	89340
EOAN	E.ON SE	-0.001	0.711	18680.04	-0.001	0.734	17811.44	21.135	31.657	4.119	0.103	2.31E-05	0.038	7296.25	3.206	162492
FME	FRESENIUS MEDI. CARE AG&CO	-0.004	1.295	5529.24	-0.004	1.255	4977.56	50.426	12.501	10.458	0.063	1.11E-04	0.054	1083.31	7.495	63798
FRE	FRESENIUS SE & CO KGAA	-0.003	1.395	4718.00	-0.003	1.340	4044.61	71.756	10.541	11.497	0.091	4.31E-05	0.054	766.95	8.237	58054
HEI	HEIDELBERGCEMENT AG	-0.002	1.207	6811.21	-0.002	1.187	6304.70	48.673	12.508	7.588	0.042	7.74E-05	0.053	1087.48	5.360	87993
HEN3	HENKEL AG & CO KGAA	-0.002	1.132	6545.63	-0.002	1.099	5879.23	48.420	12.867	9.158	0.056	7.46E-05	0.050	1158.31	6.582	72924
IFX	INFINEON TECHNOLOGIES AG	-0.001	1.151	9877.57	-0.001	1.122	9138.23	7.981	34.737	5.842	0.069	-1.67E-05	0.048	9296.21	4.398	114489
LHA	DEUTSCHE LUFTHANSA AG	-0.002	1.377	6134.45	-0.003	1.342	5427.56	15.175	27.578	9.089	0.137	-3.61E-05	0.064	6091.94	6.739	73541
LIN	LINDE AG	-0.004	1.235	4681.83	-0.005	1.224	4416.33	118.517	11.713	13.243	0.148	3.14E-05	0.070	992.44	10.121	50423
MAN	MAN SE	-0.001	1.062	7514.01	-0.001	1.053	7135.58	97.006	12.232	6.750	0.083	2.34E-05	0.037	1106.32	4.826	99017
MEO	METRO AG	-0.002	1.017	6838.59	-0.002	1.003	6221.48	46.744	13.293	8.636	0.061	6.50E-05	0.041	1373.47	6.274	77318
MRK	MERCK KGAA	-0.003	1.284	4182.83	-0.004	1.253	3631.55	75.083	10.443	11.001	0.069	-3.22E-05	0.048	767.10	8.249	60695
MUV2	MUNICH RE CO	-0.001	1.095	7549.85	-0.002	1.095	6793.82	109.627	13.150	11.682	0.143	3.45E-05	0.067	1253.04	9.119	57165
RWE	RWE AG	-0.001	0.886	9161.78	-0.002	0.887	9008.22	42.331	17.355	6.244	0.074	-3.46E-06	0.034	2166.79	4.904	107040
SAP	SAP SE	-0.001	0.732	14133.88	-0.001	0.728	13145.30	43.602	18.146	4.986	0.055	3.35E-05	0.030	2406.68	3.762	134138
SDF	K&S AG	-0.001	1.270	8268.79	-0.001	1.236	7556.92	53.451	13.948	7.631	0.074	-3.71E-05	0.050	1434.91	5.579	87592
SIE	SIEMENS AG	-0.001	0.766	17187.83	-0.001	0.755	16538.44	93.467	14.163	3.909	0.054	-1.26E-05	0.029	1497.27	3.071	171294
TKA	THYSSENKRUPP AG	-0.002	1.134	9497.21	-0.002	1.104	8676.30	32.318	18.226	6.164	0.075	-2.38E-06	0.045	2444.94	4.521	108403
VOW3	VOLKSWAGEN AG	-0.002	1.340	7032.66	-0.003	1.327	6442.13	127.090	13.133	7.723	0.176	6.93E-05	0.066	1263.04	5.775	86635

The table reports the summary statistics for Z^{Low}, Z^{High}, durations and market-related variables for the 30 stocks of the DAX. Avg.Price is the monthly average transaction prices. Avg.Volume relates the monthly average transaction volumes. Avg.Trd.dur and Avg.Qte.dur are the average trade durations and quote durations, respectively. Avg.Delta Spread is the monthly average best ask-bid spread. Avg.AvSpread relates to the average of the average last ten spread during the month. Avg.Sign.vol is the average trade imbalance based on the last ten transactions. Avg.Back.dur is the average back durations during the month. Finally, the Nb.Obs is the number of observations for the month of May 2011. We use 1/2 basis points as one unit of liquidity change.

Table 2: Estimation Results for EWS Activity Factor of EWS^{High}

	GLARMA					Market-related variables							
	γ_1^A	γ_2^A	λ_1^A	λ_2^A	Const	Exp.Tr.Dur.	Exp.Quo.Dur.	Del.Spread	Ave.Spread	Sqrt(Vol)	Abs(sign.vol)	Back.Quo.Dur	ΔEWS
ADS	1.387***	-0.404***	0.348***	-0.316***	-1.924***	-0.006	-0.061***	-2.851***	7.776***	0.4260***	0.000	0.007***	0.010
ALV	1.252***	-0.283***	0.708***	-0.637***	-2.201***	0.098***	-0.168***	1.733***	7.433***	0.3033***	-0.065***	0.019***	-0.018**
BAS	0.881***		0.368***	-0.227***	-1.648***	0.004	-0.040***	-4.402***	7.877***	0.3484***	-0.009	0.018***	-0.018**
BAYN	0.928***		0.353***	-0.273***	-1.789***	-0.011	-0.046***	-4.035***	8.702***	0.4774***	0.025	0.008***	-0.018*
BEI	0.826***		0.311***	-0.132***	-1.341***	0.027	-0.033***	-1.346**	6.268***	0.3840***	-0.028*	0.001	-0.001
BMW	1.398***	-0.409***	0.330***	-0.310***	-1.860***	-0.014	-0.048***	-2.769***	6.968***	0.4064***	-0.004	0.014***	0.000
CBK	0.869***		0.399***	-0.225***	-1.562***	-0.014	-0.016***	-1.765***	7.628***	0.4573***	-0.019	0.009***	0.016**
DAI	1.224***	-0.253***	0.380***	-0.340***	-1.864***	-0.040***	-0.036***	-5.217***	7.744***	0.4796***	0.002	0.014***	-0.013
DB1	0.941***		0.407***	-0.284***	-1.875***	0.020*	-0.023	-3.313***	6.930***	0.3417***	-0.025	0.006***	0.017*
DBK	0.841***		0.431***	-0.232***	-1.897***	-0.048***	-0.045***	-3.985***	8.663***	0.4505***	0.001	0.018***	-0.034***
DPW	0.860***		0.442***	-0.280***	-1.773***	0.040**	-0.032***	-2.761***	8.733***	0.5238***	0.024	0.007***	-0.017*
DTE	1.182***	-0.234***	0.763***	-0.665***	-2.817***	0.190***	-0.229***	3.270***	14.267***	0.4168***	0.026*	0.010***	-0.022**
EOAN	1.187***	-0.211***	0.448***	-0.402***	-2.281***	0.078***	-0.110***	4.958***	17.052***	0.3071***	0.001	0.020***	0.003
FME	0.924***		0.319***	-0.204***	-1.763***	-0.001	-0.064***	-2.560***	8.546***	0.4173***	0.012	0.007***	0.005
FRE	0.823***		0.364***	-0.147***	-1.372***	0.016	-0.069***	-0.668	5.552***	0.2938***	-0.052***	0.006***	-0.005
HEI	0.973***		0.399***	-0.338***	-1.845***	0.039***	-0.046***	-2.774***	5.341***	0.3440***	0.007	0.004***	-0.001
HEN3	0.937***		0.386***	-0.280***	-1.689***	0.026*	-0.085***	-0.677	5.145***	0.3635***	0.013	0.005***	-0.026***
IFX	0.882***		0.360***	-0.199***	-1.589***	0.030***	-0.065***	-1.251***	5.395***	0.4075***	-0.004	0.012***	0.001
LHA	0.546***		0.352***	-0.002	-1.271***	0.106***	-0.072***	-0.465	7.832***	0.4189***	0.012	0.009***	-0.001
LIN	0.692***		0.411***	-0.152***	-1.318***	0.132***	-0.098***	3.000***	8.557***	0.2682***	-0.095***	0.004***	0.001
MAN	1.430***	-0.437***	0.431***	-0.411***	-2.192***	-0.008	-0.059***	-2.238***	5.677***	0.2949***	-0.013	0.005***	-0.006
MEO	0.866***		0.368***	-0.190***	-1.613***	0.060***	-0.055***	-0.182	7.053***	0.3868***	-0.006	0.008***	-0.025**
MRK	0.790***		0.234***	-0.050	-1.375***	0.047***	-0.098***	-1.965***	7.953***	0.3162***	-0.021	0.006***	0.011
MUV2	0.466***		0.498***	-0.053	-1.954***	0.149***	-0.160***	2.123***	12.121***	0.4819***	-0.003	0.006***	-0.042***
RWE	0.930***		0.438***	-0.326***	-1.758***	-0.024*	-0.034***	-2.986***	3.889***	0.3899***	0.008	0.006***	-0.033***
SAP	0.919***		0.461***	-0.338***	-1.893***	-0.032***	-0.039***	-2.918***	6.663***	0.3861***	-0.040***	0.007***	-0.061***
SDF	0.895***		0.321***	-0.193***	-1.521***	0.005	-0.025***	-3.336***	7.833***	0.4431***	0.001	0.009***	0.025***
SIE	0.923***		0.442***	-0.334***	-1.833***	-0.054***	-0.045***	-4.464***	5.258***	0.3932***	-0.015	0.010***	-0.071***
TKA	1.439***	-0.453***	0.340***	-0.316***	-1.704***	0.018*	-0.038***	-2.242***	5.777***	0.4170***	-0.011	0.009***	-0.012
VOW3	0.865***		0.372***	-0.214***	-1.443***	-0.022*	-0.044***	-2.300***	6.018***	0.437***	-0.015	0.013***	0.010
Mean	$\sum \gamma_j^A$: 0.880		$\sum \lambda_j^A$: 0.137		-1.765	0.027	-0.066	-1.613	7.688	0.393	-0.010	0.009	-0.011
Median	$\sum \gamma_j^A$: 0.921		$\sum \lambda_j^A$: 0.122		-1.768	0.017	-0.047	-2.271	7.530	0.400	-0.004	0.008	-0.005
Min	$\sum \gamma_j^A$: 0.466		$\sum \lambda_j^A$: 0.019		-2.817	-0.054	-0.229	-5.217	3.889	0.268	-0.095	0.001	-0.071
Max	$\sum \gamma_j^A$: 0.993		$\sum \lambda_j^A$: 0.445		-1.271	0.190	-0.016	4.958	17.052	0.524	0.026	0.020	0.025

The table reports the estimated results for the activity factor of Z^{high} and the distribution of the estimated parameters. γ^A and λ^A are parameters for GLARMA structure $g_k^A = \sum_{j=1}^{p} \gamma_j^A g_{k-j}^A + \sum_{j=1}^{l} \lambda_j^A A_{k-j}$, and market-related variables include variables capturing duration, volume and liquidity of the market. For the sake of brevity, we do not present the estimation results of seasonality dummy variables. They are available from the authors. ***, ** and * denote either coefficient estimates that are significantly different from zero or test statistics that are significant at the 1%, 5% and 10%, respectively.

Table 3: In-sample tests for EWS Activity Factor of EWS^{High}

Ticker	LB(5)	LB(10)	LB(15)	R-sqrt	ROC	#_Acc
ADS	2.219	18.049	20.659	19.78%	0.615	58.73%
ALV	23.910	34.506	38.613	34.15%	0.660	65.06%
BAS	14.154	33.652	38.929	32.10%	0.587	63.53%
BAYN	10.666	22.667	24.255	30.38%	0.599	62.57%
BEI	5.411	10.839	11.966	14.82%	0.590	57.70%
BMW	11.554	17.168	18.734	24.62%	0.594	59.29%
CBK	19.949	33.050	38.978	18.50%	0.614	58.74%
DAI	7.139	14.472	32.525	27.86%	0.606	61.62%
DB1	20.473	29.478	34.399	23.36%	0.622	60.08%
DBK	31.151	44.858	50.491	33.94%	0.612	65.02%
DPW	4.399	9.066	12.763	18.57%	0.624	59.53%
DTE	29.413	33.743	40.079	34.93%	0.687	65.59%
EOAN	16.660	25.716	33.443	35.16%	0.630	65.50%
FME	17.637	27.650	30.790	16.99%	0.629	59.98%
FRE	2.116	8.552	11.042	16.12%	0.605	58.41%
HEI	41.532	47.404	47.918	18.84%	0.612	59.04%
HEN3	25.981	34.059	41.970	21.50%	0.610	59.01%
IFX	15.971	22.613	30.628	20.74%	0.602	58.15%
LHA	1.313	5.738	17.694	14.31%	0.605	58.72%
LIN	3.200	6.844	17.650	14.57%	0.603	58.99%
MAN	11.935	33.929	43.124	27.94%	0.630	62.11%
MEO	13.448	24.031	30.312	24.36%	0.605	59.42%
MRK	7.958	16.057	18.399	18.64%	0.596	57.46%
MUV2	3.545	8.215	11.460	18.98%	0.627	59.54%
RWE	21.055	29.173	34.746	30.86%	0.597	62.97%
SAP	28.433	35.577	38.050	36.15%	0.598	66.49%
SDF	11.341	15.949	27.857	17.48%	0.608	58.57%
SIE	26.444	34.276	44.310	35.94%	0.596	66.29%
TKA	5.540	7.880	10.932	22.79%	0.604	58.95%
VOW3	17.429	20.236	30.089	13.61%	0.603	58.99%
Mean	15.066	23.515	29.427	23.93%	0.612	60.87%
Median	13.801	23.349	30.709	22.15%	0.606	59.47%
Min	1.313	5.738	10.932	13.61%	0.587	57.46%
Max	41.532	47.404	50.491	36.15%	0.687	66.49%

The table reports the results of in-sample tests for the model of the activity factor. LB(5), LB(10) and LB(15) are Ljung-Box statistics on 5, 10 and 15 lagged standardized residuals. The critical value for LB(5), LB(10), and LB(15), are 11.07, 18.30 and 24.99, respectively. R-sqrt is the McFadden's R squared, defined as $R^2_{McFaden} = 1 - \frac{log(L_c)}{log(L_{null})}$ where L_c denotes the likelihood value from the current fitted model and L_{null} denotes the corresponding value for the null model. ROC relates the Receiver Operating Characteristic test. #_Acc is the Count accuracy that takes 50% as the threshold to have value one.

Table 4: Estimation Results for Direction Factor of EWS^{High}

	GLARMA				Market-related variables							
	γ_1^D	γ_2^D	λ_1^D	λ_2^D	Const	Exp.QQ.Dur.	Del.Spread	Ave.Spread	Sqrt(Vol)	Abs(sign.vol)	Back.Quo.Dur	ΔEWS
ADS	0.651***		-1.035***	0.134***	0.313***	-0.003	18.849***	-16.959***	0.395***	-0.0278	-0.016***	-0.116***
ALV	0.947***	-0.190*	-1.751***	0.778**	0.374***	0.017***	13.873***	-14.755***	0.270***	-0.0888***	-0.021***	-0.235***
BAS	-0.262***	0.505***	-1.786***	-1.448***	0.683***	-0.014***	26.006***	-25.987***	0.210***	-0.0954***	-0.044***	-0.131***
BAYN	-0.234***	0.513***	-1.819***	-1.422***	0.497***	-0.013**	20.205***	-25.366***	0.340***	-0.0413	-0.027***	-0.070***
BEI	0.630***		-0.945***	0.076**	0.548***	-0.011*	16.483***	-15.537***	0.349***	-0.0122	-0.009***	-0.089***
BMW	0.672***		-1.387***	0.193***	0.456***	-0.002	20.841***	-20.680***	0.287***	-0.0324**	-0.028***	-0.143***
CBK	0.612***		-0.980***	0.081***	0.330***	0.007*	15.190***	-14.093***	0.460***	-0.0053	-0.033***	-0.115***
DAI	0.678***		-1.652***	0.254***	0.743***	-0.006	21.453***	-26.147***	0.307***	-0.0212	-0.039***	-0.122***
DB1	0.694***		-1.184***	0.241***	0.290***	0.006	18.165***	-13.134***	0.268***	-0.0954***	-0.018***	-0.073***
DBK	-0.303***	0.468***	-1.743***	-1.385***	0.572***	0.001	20.194***	-26.719***	0.322***	0.0039	-0.036***	-0.038***
DPW	0.636***		-1.098***	0.087**	0.393***	-0.006	15.274***	-14.188***	0.338***	-0.0396	-0.011***	-0.139***
DTE	0.540***		-1.561***	0.086*	0.654***	-0.005	13.334***	-17.076***	0.351***	-0.0729***	-0.010***	-0.251***
EOAN	-0.326***	0.536***	-2.169***	-1.833***	1.016***	0.005	18.808***	-29.449***	0.289***	0.0259	-0.021***	-0.031*
FME	0.703***		-0.913***	0.166***	0.014	-0.019***	18.891***	-11.607***	0.533***	-0.0160	-0.016***	-0.076***
FRE	0.637***		-0.816***	0.091**	0.318***	-0.017***	17.374***	-11.882***	0.401***	-0.0437*	-0.012***	-0.143***
HEI	0.702***		-0.978***	0.191***	0.285***	0.000	16.810***	-12.642***	0.410***	-0.0484**	-0.022***	-0.082***
HEN3	0.674***		-1.043***	0.148***	0.262***	-0.002	18.092***	-14.298***	0.403***	-0.0635***	-0.016***	-0.093***
IFX	0.663***		-1.020***	0.128***	0.385***	0.004	19.106***	-17.792***	0.361***	-0.0296	-0.020***	-0.143***
LHA	0.627***		-0.907***	0.071**	0.183***	0.006	15.379***	-12.404***	0.446***	-0.0638***	-0.012***	-0.132***
LIN	0.611***		-1.152***	0.088**	0.398***	0.003	13.156***	-13.895***	0.399***	-0.1355***	-0.007***	-0.149***
MAN	0.731***		-1.203***	0.367***	0.371***	-0.001	20.971***	-14.168***	0.280***	-0.0670***	-0.023***	-0.042***
MEO	0.671***		-1.223***	0.239***	0.331***	-0.014***	21.018***	-18.439***	0.359***	-0.1166***	-0.020***	-0.106***
MRK	0.712***		-1.039***	0.180***	0.083	-0.013**	18.297***	-15.486***	0.488***	-0.0460*	-0.014***	-0.117***
MUV2	0.553***		-1.476***	0.005	0.546***	0.006	10.676***	-17.681***	0.481***	-0.0598**	-0.006***	-0.289***
RWE	0.690***		-1.807***	0.350***	0.339***	-0.010*	20.681***	-22.031***	0.382***	-0.0385	-0.019***	-0.031*
SAP	-0.262***	0.511***	-2.038***	-1.617***	0.609***	-0.016***	22.845***	-27.469***	0.254***	-0.0101	-0.029***	-0.038*
SDF	0.688***		-0.901***	0.099***	0.292***	0.001	15.747***	-16.008***	0.453***	-0.0385**	-0.023***	-0.133***
SIE	-0.096**	0.434***	-2.083***	-1.290***	0.760***	-0.012**	21.702***	-33.457***	0.270***	-0.0234	-0.037***	-0.039***
TKA	0.689***		-1.169***	0.223***	0.350***	0.010**	19.227***	-16.906***	0.349***	-0.0437**	-0.019***	-0.094***
VOW3	0.590***		-0.958***	0.043	0.515***	-0.008*	13.693***	-15.683***	0.409***	-0.049***	-0.016***	-0.128***
Mean	$\sum \gamma_j^D$: 0.577		$\sum \lambda_j^D$: -1.484		0.430	-0.003	18.078	-18.398	0.362	-0.047	-0.021	-0.113
Median	$\sum \gamma_j^D$: 0.644		$\sum \lambda_j^D$: -0.960		0.379	-0.003	18.552	-16.457	0.355	-0.042	-0.020	-0.115
Min	$\sum \gamma_j^D$: 0.165		$\sum \lambda_j^D$: -4.003		0.014	-0.019	10.676	-33.457	0.210	-0.136	-0.044	-0.289
Max	$\sum \gamma_j^D$: 0.757		$\sum \lambda_j^D$: -0.725		1.016	0.017	26.006	-11.607	0.533	0.026	-0.006	-0.031

The table reports the estimated results for the direction factor of Z^{high} and the distribution of the estimated parameters. γ^D and λ^D are parameters for GLARMA structure: $g_k^D = \sum_{j=1}^{p} \gamma_j^D g_{k-j}^D + \sum_{j=1}^{l} \lambda_j^D D_{k-j}$, and market-related variables include variables capturing duration, volume and liquidity of the market. For the sake of brevity, we do not present the estimation results of seasonality dummy variables. They are available from the authors. ***, ** and * denote either coefficient estimates that are significantly different from zero or test statistics that are significant at the 1%, 5% and 10%, respectively.

Table 5: In-sample tests for EWS Direction Factor of EWS^{High}

Ticker	LB(5)	LB(10)	LB(15)	R-sqrt	ROC	#_Acc
ADS	16.754	19.629	26.579	30.20%	0.770	70.65%
ALV	9.259	24.103	31.341	41.14%	0.844	78.05%
BAS	30.498	45.739	63.983	39.66%	0.841	76.88%
BAYN	19.822	25.668	29.043	40.42%	0.845	77.41%
BEI	19.277	22.232	27.909	28.30%	0.754	69.05%
BMW	21.935	31.971	35.402	34.46%	0.804	73.80%
CBK	9.092	17.837	21.840	29.10%	0.759	69.67%
DAI	11.084	20.910	27.211	38.34%	0.831	76.05%
DB1	3.546	17.957	23.505	30.68%	0.778	71.34%
DBK	21.048	35.665	43.608	38.82%	0.835	76.58%
DPW	2.831	21.182	28.870	31.58%	0.779	71.32%
DTE	9.281	12.901	14.393	39.02%	0.833	76.93%
EOAN	43.588	46.919	52.397	48.66%	0.882	81.79%
FME	16.364	24.499	29.680	28.80%	0.758	69.61%
FRE	1.820	14.510	21.628	27.31%	0.751	69.12%
HEI	13.450	18.759	25.374	28.34%	0.758	69.81%
HEN3	13.724	16.294	19.716	29.23%	0.764	70.14%
IFX	4.792	7.171	13.140	30.65%	0.771	70.55%
LHA	14.649	17.871	23.206	28.81%	0.758	69.21%
LIN	12.634	19.696	29.718	31.71%	0.782	71.56%
MAN	11.587	21.958	38.927	30.38%	0.777	71.32%
MEO	2.430	18.065	23.143	31.79%	0.787	71.91%
MRK	5.961	9.387	18.079	30.33%	0.771	70.81%
MUV2	4.066	14.645	17.324	39.25%	0.831	76.81%
RWE	7.134	13.275	18.429	39.18%	0.837	76.87%
SAP	22.690	35.837	47.941	43.09%	0.861	79.22%
SDF	4.687	9.073	11.193	28.84%	0.760	69.61%
SIE	35.774	41.509	45.035	43.37%	0.862	79.12%
TKA	9.923	15.957	19.692	31.17%	0.779	71.56%
VOW3	10.233	24.396	39.770	28.87%	0.761	69.48%
Mean	13.664	22.187	28.936	34.05%	0.797	73.21%
Median	11.335	19.662	26.895	31.37%	0.779	71.45%
Min	1.820	7.171	11.193	27.31%	0.751	69.05%
Max	43.588	46.919	63.983	48.66%	0.882	81.79%

The table reports the results of in-sample tests for the model of the direction factor. LB(5), LB(10) and LB(15) are Ljung-Box statistics on 5, 10 and 15 lagged standardized residuals. The critical value for LB(5), LB(10), LB(15), are 11.07, 18.30 and 24.99, respectively. R-sqrt is the McFadden's R squared, defined as $R^2_{McFaden} = 1 - \frac{log(L_c)}{log(L_{null})}$ where L_c denotes the likelihood value from the current fitted model and L_{null} denotes the corresponding value for the null model. ROC relates the Receiver Operating Characteristic test. #_Acc is the Count accuracy that takes 50% as the threshold to have value one.

Table 6: Estimation Results for Liquidity Size Factor of EWS^{High}

	GLARMA								Market-related variables							
	γ_1^{Siz}	γ_2^{Siz}	γ_3^{Siz}	γ_4^{Siz}	λ_1^{Siz}	λ_2^{Siz}	λ_3^{Siz}	λ_4^{Siz}	Const	Exp.QQ.Dur.	Del.Spread	Ave.Spread	Sqrt(Vol)	Abs(sign.vol)	Back.Quo.Dur	ΔEWS
ADS	0.856***				-0.268***	0.161***			2.546***	0.003***	1.864***	-8.093***	-0.343***	-0.046*	0.007***	0.011
ALV	0.591***	0.255***			-0.400***	0.260***			2.640***	0.002***	-0.952*	-12.652***	-0.190***	-0.114***	0.007**	-0.072***
BAS	0.915***				-0.467***	0.353***			3.167***	0.006***	2.471***	-10.282***	-0.345***	-0.053***	0.039***	0.067***
BAYN	0.912***				-0.403***	0.298***			3.734***	0.001	0.216	-8.057***	-0.403***	-0.182***	0.022***	0.035**
BEI	0.837***				-0.243***	0.145***			2.139***	0.001***	2.186***	-4.874***	-0.349***	0.011	0.003***	0.020**
BMW	0.914***				-0.398***	0.298***			2.953***	0.005***	2.268***	-6.859***	-0.385***	-0.020	0.018***	0.068***
CBK	0.921***				-0.226***	0.162***			2.127***	0.004***	1.641***	-5.094***	-0.297***	-0.127***	0.021***	0.007
DAI	0.903***				-0.408***	0.299***			3.293***	0.002***	1.338**	-8.661***	-0.385***	-0.045***	0.029***	0.060***
DB1	0.868***				-0.197***	0.100***			2.506***	0.002***	1.463**	-6.388***	-0.338***	-0.023	0.008***	0.038***
DBK	0.774***	0.096***			-0.427***	0.302***			3.281***	0.008***	2.019***	-9.528***	-0.414***	-0.063***	0.031***	0.078***
DPW	0.913***				-0.332***	0.265***			2.010***	0.001**	-1.270**	-3.256***	-0.261***	-0.019	0.003**	0.011
DTE	0.931***				-0.381***	0.322***			1.814***	0.002***	-2.502***	-4.058***	-0.087***	-0.026	0.005**	-0.086***
EOAN	0.491***	0.350***			-0.398***	0.190***			3.643***	0.013***	-2.273***	-21.821***	-0.271***	-0.130***	0.042***	0.008
FME	0.903***				-0.200***	0.143***			2.554***	0.003***	1.228***	-9.827***	-0.266***	-0.015	0.001	0.007
FRE	0.814***				-0.201***	0.099***			1.853***	0.002***	1.640***	-5.127***	-0.301***	-0.025	0.005***	0.017***
HEI	0.830***				-0.201***	0.087***			2.161***	0.002***	0.856**	-5.217***	-0.305***	-0.049***	0.005***	0.041***
HEN3	0.845***				-0.281***	0.158***			2.697***	0.002***	-0.121	-6.790***	-0.354***	-0.067***	0.003***	0.022***
IFX	0.915***				-0.289***	0.213***			2.334***	0.004***	1.154***	-5.023***	-0.260***	-0.077***	0.008***	0.031***
LHA	0.887***				-0.201***	0.140***			2.010***	0.001***	0.995***	-4.672***	-0.251***	-0.039*	0.003***	0.019***
LIN	0.900***				-0.284***	0.230***			1.997***	0.001	-0.291	-5.429***	-0.191***	-0.046	0.002	-0.059***
MAN	-0.357***	1.469***	0.354***	-0.495***	-0.159***	-0.133***	0.145***	0.122***	2.729***	0.004***	2.364***	-7.037***	-0.364***	-0.110***	0.011***	0.017***
MEO	0.841***				-0.283***	0.157***			2.828***	0.003***	1.577**	-7.947***	-0.388***	-0.075**	0.004***	0.050***
MRK	0.807***				-0.210***	0.110***			2.753***	0.002***	2.171***	-4.589***	-0.355***	-0.033	0.004***	0.043***
MUV2	0.875***				-0.309***	0.214***			1.858***	0.001	-1.543***	-4.321***	-0.160***	-0.021	0.001	-0.063***
RWE	0.841***				-0.337***	0.208***			3.219***	0.005***	2.160**	-5.695***	-0.442***	-0.107***	0.018***	0.067***
SAP	0.936***				-0.531***	0.415***			3.923***	0.003***	0.487	-11.225***	-0.321***	-0.075***	0.022***	0.136***
SDF	0.893***				-0.210***	0.136***			2.209***	0.002***	1.889***	-6.107***	-0.355***	-0.048***	0.007***	0.044***
SIE	0.754***	0.122***			-0.415***	0.267***			3.532***	0.007***	2.136**	-8.194***	-0.357***	-0.065***	0.042***	0.039***
TKA	0.893***				-0.224***	0.150***			2.527***	0.003***	1.736***	-6.370***	-0.355***	-0.105***	0.008***	0.042***
VOW3	0.893***				-0.190***	0.129***			1.853***	0.001**	0.846**	-3.012***	-0.271***	-0.008	0.006***	0.007
Mean	$\sum \gamma_j^{Siz}$: 0.882				$\sum \lambda_j^{Siz}$: -0.098				2.630	0.003	0.925	-7.207	-0.312	-0.060	0.013	0.024
Median	$\sum \gamma_j^{Siz}$: 0.882				$\sum \lambda_j^{Siz}$: -0.097				2.550	0.002	1.400	-6.379	-0.340	-0.048	0.007	0.027
Min	$\sum \gamma_j^{Siz}$: 0.884				$\sum \lambda_j^{Siz}$: -0.096				1.814	0.001	-2.502	-21.821	-0.442	-0.182	0.001	-0.086
Max	$\sum \gamma_j^{Siz}$: 0.883				$\sum \lambda_j^{Siz}$: -0.095				3.923	0.013	2.471	-3.012	-0.087	0.011	0.042	0.136

The table reports the estimated results for the model of the size factor of Z^{high} and the distribution of the estimated parameters. γ^{Siz} and λ^{Siz} are parameters for GLARMA structure: $g_k^{Siz} = \sum_{j=1}^{p} \gamma_j^{Siz} g_{k-j}^{Siz} + \sum_{j=1}^{l} \lambda_j^{Siz} s_{k-j}$, and market-related variables include variables capturing duration, volume and liquidity of the market. For the sake of brevity, we do not present the estimation results of seasonality dummy variables. They are available from the authors. ***, ** and * denote either coefficient estimates that are significantly different from zero or test statistics that are significant at the 1%, 5% and 10%, respectively.

Table 7: Ljung-Box Statistics for EWS Size Factor of EWS^{High}

Ticker	LB(5)	LB(10)	LB(15)	R-sqrt
ADS	95.70	108.80	130.70	33.73%
ALV	287.19	305.70	315.16	6.41%
BAS	221.41	260.39	309.56	6.77%
BAYN	176.57	200.02	211.18	3.21%
BEI	65.05	70.04	87.39	44.55%
BMW	222.37	244.43	274.53	12.69%
CBK	106.83	124.26	135.49	33.76%
DAI	177.17	195.01	207.04	9.40%
DB1	209.51	226.88	248.07	18.36%
DBK	326.86	350.42	386.83	48.26%
DPW	37.58	41.47	44.18	37.99%
DTE	185.71	188.59	192.32	37.26%
EOAN	343.36	398.26	493.74	26.25%
FME	153.91	189.04	196.94	34.72%
FRE	44.18	47.81	61.49	47.51%
HEI	180.14	204.21	233.65	20.43%
HEN3	158.55	171.83	176.75	6.54%
IFX	108.84	113.37	128.35	31.57%
LHA	73.14	79.96	101.33	40.91%
LIN	43.30	45.34	52.43	39.20%
MAN	421.59	539.34	635.15	20.27%
MEO	86.72	123.41	140.14	40.63%
MRK	145.52	169.79	181.95	66.15%
MUV2	167.49	172.99	179.35	42.68%
RWE	242.26	269.68	288.75	12.41%
SAP	191.95	217.20	233.29	30.90%
SDF	143.78	163.63	175.70	34.37%
SIE	416.45	474.87	515.65	6.31%
TKA	248.86	279.60	298.74	22.68%
VOW3	82.97	87.87	107.47	50.63%
Mean	178.83	202.14	224.78	28.88%
Median	172.03	188.82	194.63	32.65%
Min	37.58	41.47	44.18	3.21%
Max	421.59	539.34	635.15	66.15%

The table reports the results of Ljung-Box statistics on 5, 10 and 15 lagged standardized residuals and adjusted R^2. The critical value for LB(5), LB(10), and LB(15), are 11.07, 18.30 and 24.99, respectively.

Table 8: Effect of Key Market-related Variables on EWS

	Activity	Direction	Size	Total Effect on Ex-ante Weighted Spread
Square root(vol)	+/+	+/+	- /-	If the trade volume increases, both ΔEWS^{High} and ΔEWS^{Low} are likely to increase; the size of this increase is likely to be large.
Abs(sign.vol)	no.sig/-	- /-	-/-	If imbalance of trade increases, the ΔEWS^{Low} is likely to remain the same, however, if imbalance is small, the ΔEWS^{Low} is likely to slightly increase. For the higher-level of LOB, the dynamic seems that ΔEWS^{High} does not depend on the imbalance of trade.
Ave_spread	+/+	- /-	-/-	If Ave_Spread increases, the both the EWS^{High} and EWS^{Low} are likely to decrease, and the size of this decrease is likely to be large.
Delta_spread	-/+	+/+	+/+	For lower-level of LOB, higher Delta_spread is likely to lead to a slightly lower liquidity. However, the higher-level of LOB is likely to be stable after the changes in Delta_spread.

The table summarizes the effect of various market-related variables on the EWS^{high} and EWS^{low}. +/- means positive and negative effect of corresponding factor on the EWS^{high} and EWS^{low}.

Table 9: Out-of-sample Test for Unconditional Distribution

	$\tilde{Z}^{High}=0$	$\tilde{Z}^{High}=Z^{High}$		$\tilde{Z}^{Low}=0$	$\tilde{Z}^{Low}=Z^{Low}$	
	p-value0	p-value1	p-value2	p-value0	p-value1	p-value2
ADS	0.685	0.703	**<0.001**	0.069	0.169	**0.048**
ALV	**<0.001**	**0.001**	0.224	0.109	0.197	0.282
BAS	0.374	0.641	0.308	0.606	0.652	0.439
BAYN	0.671	0.836	**0.041**	0.246	0.452	0.131
BEI	0.214	0.115	**0.002**	0.055	0.064	**0.006**
BMW	0.539	0.769	0.573	0.578	0.609	0.452
CBK	**0.035**	0.140	0.128	**0.003**	**0.013**	**<0.001**
DAI	0.244	0.351	0.296	0.092	0.134	**0.015**
DB1	0.382	0.692	0.457	0.288	0.316	**0.007**
DBK	0.561	0.662	**<0.001**	0.371	0.493	**0.046**
DPW	0.684	0.773	0.492	0.476	0.568	0.061
DTE	0.713	0.728	0.617	**0.011**	**0.044**	**<0.001**
EOAN	0.557	0.693	**0.042**	0.182	0.208	**0.020**
FME	0.091	0.127	0.151	**<0.001**	**<0.001**	**<0.001**
FRE	**0.003**	0.031	**<0.001**	**<0.001**	**0.007**	**<0.001**
HEI	**0.011**	**0.041**	**0.008**	**0.003**	**0.005**	**<0.001**
HEN3	0.452	0.406	0.182	**0.001**	**0.018**	**0.021**
IFX	0.638	0.722	0.351	**<0.001**	**0.030**	**0.001**
LHA	0.261	0.602	0.171	0.633	0.740	**0.009**
LIN	0.578	0.768	0.246	0.594	0.571	0.387
MAN	0.038	0.056	**<0.001**	**0.002**	**0.004**	**<0.001**
MEO	0.193	0.214	0.164	**0.010**	**0.022**	**<0.001**
MRK	0.280	0.363	0.092	**0.006**	0.062	**<0.001**
MUV2	0.332	0.620	**<0.001**	0.392	0.602	0.176
RWE	0.719	0.731	0.063	0.605	0.628	**0.023**
SAP	0.565	0.524	0.051	0.546	0.538	**0.038**
SDF	0.670	0.783	0.072	0.335	0.454	0.392
SIE	0.567	0.601	**<0.001**	0.389	0.447	**0.021**
TKA	0.700	0.786	0.391	0.228	0.243	0.075
VOW3	0.446	0.758	0.376	0.197	0.563	0.134
Mean	0.508	0.508	0.183	0.234	0.295	0.093
Median	0.631	0.631	0.139	0.190	0.226	0.021
Min	<0.001	0.001	<0.001	<0.001	<0.001	<0.001
Max	0.836	0.836	0.617	0.633	0.740	0.452

The table presents the p-values of the one-sample t-test (p-value0), two-sample t-test (p-value1) and Pearson's chi-square goodness-of-fit test (p-value2) between the real time series and the simulated one for 30 stocks in DAX30 in the third week of May 2011. The null hypothesis for the one-sample t-test is that the means of the sample is equal to zero. The null hypothesis for the two-sample t-test is that the means of the two samples are equal. The null hypothesis for Pearson's chi-square goodness-of-fit is that the two categorized samples have the same distribution. For Pearson's chi-square goodness-of-fit test, we categorize the simulated data into three groups: less than zero, zero and greater than zero. The bold entries are the p-values smaller than 5%.

Table 10: Empirical and Simulated Autocorrelation Functions

	Empirical ACFs					Simulated ACFs				
Ticker	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	$\hat{\rho}_1$	$\hat{\rho}_2$	$\hat{\rho}_3$	$\hat{\rho}_4$	$\hat{\rho}_5$
ADS	-0.205*	-0.085*	-0.076*	-0.003	-0.029*	-0.145*	-0.078*	-0.049*	-0.031*	-0.021
ALV	-0.264*	-0.087*	-0.045*	-0.012*	-0.006	-0.260*	-0.076*	-0.035*	-0.018*	-0.010
BAS	-0.229*	-0.122*	-0.038*	-0.006	-0.059*	-0.239*	-0.087*	-0.041*	-0.021*	-0.011
BAYN	-0.281*	-0.107*	-0.035*	-0.005	-0.022*	-0.255*	-0.081*	-0.037*	-0.019*	-0.011
BEI	-0.170*	-0.089*	-0.042*	-0.052*	-0.055*	-0.160*	-0.078*	-0.044*	-0.027	-0.018
BMW	-0.245*	-0.060*	-0.038*	-0.067*	-0.013*	-0.220*	-0.087*	-0.042*	-0.022*	-0.013
CBK	-0.206*	-0.117*	-0.063*	-0.026*	-0.029*	-0.143*	-0.076*	-0.045*	-0.027*	-0.017*
DAI	-0.274*	-0.089*	-0.031*	-0.022*	-0.023*	-0.248*	-0.086*	-0.041*	-0.022*	-0.012
DB1	-0.225*	-0.123*	-0.057*	-0.013	-0.015*	-0.176*	-0.082*	-0.044*	-0.026*	-0.017
DBK	-0.241*	-0.090*	-0.023*	-0.025*	-0.031*	-0.244*	-0.082*	-0.040*	-0.021*	-0.011
DPW	-0.226*	-0.126*	-0.035*	-0.016	-0.008	-0.182*	-0.085*	-0.043*	-0.023	-0.013
DTE	-0.244*	-0.117*	-0.051*	-0.023*	-0.013	-0.239*	-0.087*	-0.033*	-0.013	-0.006
EOAN	-0.295*	-0.105*	-0.018*	-0.013*	-0.015*	-0.285*	-0.077*	-0.034*	-0.017	-0.008
FME	-0.203*	-0.125*	-0.044*	-0.020*	-0.039*	-0.171*	-0.082*	-0.048*	-0.030*	-0.017
FRE	-0.137*	-0.138*	-0.069*	-0.032*	-0.032*	-0.107*	-0.083*	-0.052*	-0.033*	-0.020
HEI	-0.236*	-0.100*	-0.058*	-0.021*	0.006	-0.165*	-0.082*	-0.044*	-0.025*	-0.015
HEN3	-0.209*	-0.109*	-0.049*	-0.005	-0.026*	-0.173*	-0.082*	-0.046*	-0.027*	-0.017
IFX	-0.225*	-0.130*	-0.030*	-0.024*	-0.030*	-0.171*	-0.077*	-0.041*	-0.024*	-0.015
LHA	-0.214*	-0.117*	-0.046*	-0.041*	-0.024*	-0.134*	-0.076*	-0.047*	-0.029*	-0.018
LIN	-0.261*	-0.103*	-0.060*	-0.024*	-0.004	-0.175*	-0.085*	-0.047*	-0.026	-0.015
MAN	-0.289*	-0.057*	-0.053*	-0.015*	-0.038*	-0.281*	-0.074*	-0.035*	-0.020	-0.012
MEO	-0.252*	-0.113*	-0.030*	-0.010	-0.015	-0.186*	-0.083*	-0.045*	-0.026*	-0.016
MRK	-0.226*	-0.095*	-0.001	-0.059*	-0.027*	-0.176*	-0.083*	-0.045*	-0.024*	-0.014
MUV2	-0.269*	-0.103*	-0.040*	-0.023*	-0.018	-0.238*	-0.085*	-0.032*	-0.013	-0.006
RWE	-0.175*	-0.055*	-0.022*	-0.011	0.028*	-0.244*	-0.084*	-0.040*	-0.021*	-0.011
SAP	-0.274*	-0.116*	-0.028*	-0.011*	-0.033*	-0.271*	-0.084*	-0.037*	-0.019*	-0.010
SDF	-0.233*	-0.106*	-0.053*	-0.022*	-0.026*	-0.168*	-0.086*	-0.049*	-0.029*	-0.017
SIE	-0.286*	-0.088*	-0.032*	-0.047*	0.010*	-0.282*	-0.077*	-0.032*	-0.016*	-0.009
TKA	-0.255*	-0.120*	-0.015*	-0.045*	-0.004	-0.186*	-0.087*	-0.044*	-0.025*	-0.015
VOW3	-0.202*	-0.103*	-0.042*	-0.021*	-0.028*	-0.140*	-0.076*	-0.045*	-0.027*	-0.017
Mean	-0.235	-0.103	-0.041	-0.024	-0.021	-0.202	-0.082	-0.042	-0.023	-0.014
Median	-0.234	-0.105	-0.041	-0.021	-0.024	-0.184	-0.082	-0.043	-0.024	-0.014
Min	-0.295	-0.138	-0.076	-0.067	-0.059	-0.285	-0.087	-0.052	-0.033	-0.021
Max	-0.137	-0.055	-0.001	-0.003	0.028	-0.107	-0.074	-0.032	-0.013	-0.006

The table presents the empirical and simulated ACFs from 1 to 5 lags ($\rho_1 ... \rho_5$) for 30 stocks in the third week of May 2011. A given simulated ACF is the average of the ACFs for 5000 paths of simulations. * denote the autocorrelation coefficients that are significant at the 5%.

Table 11: Out-of-sample MSE for Various Horizons

Tickers	Interval (ticks)						
	5	10	30	50	100	150	200
ADS	0.30	0.73	1.72	2.26	3.55	5.74	8.94
ALV	0.16	0.43	2.20	3.49	5.06	7.50	11.33
BAS	0.14	0.38	2.03	3.66	5.50	8.01	11.84
BAYN	0.14	0.35	1.41	1.86	2.72	4.15	6.07
BEI	0.45	1.13	1.96	2.69	4.65	8.54	16.38
BMW	0.20	0.52	2.68	3.58	5.28	7.74	11.48
CBK	0.12	0.32	1.62	3.61	5.66	8.87	14.91
DAI	0.11	0.28	1.42	2.50	3.75	5.59	8.63
DB1	0.24	0.62	2.38	3.14	4.77	7.22	11.13
DBK	0.08	0.20	1.00	2.01	3.04	4.50	6.82
DPW	0.44	1.16	2.97	4.02	5.89	9.08	13.28
DTE	0.24	0.64	2.25	3.09	4.70	7.24	11.98
EOAN	0.15	0.40	1.87	2.49	3.67	5.44	8.26
FME	0.38	1.00	2.64	3.65	6.16	10.48	21.06
FRE	0.33	0.83	2.19	2.96	5.10	10.37	22.62
HEI	0.32	0.85	3.42	4.68	7.48	12.39	22.46
HEN3	0.28	0.69	1.77	2.45	3.98	6.90	12.99
IFX	0.16	0.39	1.66	2.20	3.37	5.46	9.56
LHA	0.35	0.87	2.15	2.98	4.56	6.43	10.36
LIN	0.49	1.20	2.01	2.69	4.06	5.92	9.07
MAN	0.24	0.64	2.28	3.03	4.80	7.41	13.16
MEO	0.35	0.90	2.34	3.22	4.93	8.40	14.27
MRK	0.37	0.92	2.37	3.02	4.62	7.39	11.78
MUV2	0.49	1.29	2.66	3.55	5.34	7.77	11.17
RWE	0.15	0.37	1.36	1.92	2.69	4.13	6.23
SAP	0.12	0.33	1.65	2.28	3.37	4.99	7.53
SDF	0.21	0.49	1.31	1.63	2.56	4.10	6.71
SIE	0.08	0.19	0.94	1.84	2.73	4.12	6.26
TKA	0.19	0.50	2.33	3.15	4.81	7.22	11.32
VOW3	0.29	0.72	2.04	2.69	4.17	6.53	9.84
Mean	0.25	0.64	2.02	2.88	4.43	6.99	11.58
Median	0.24	0.63	2.03	2.97	4.64	7.22	11.25
Min	0.08	0.19	0.94	1.63	2.56	4.10	6.07
Max	0.49	1.29	3.42	4.68	7.48	12.39	22.62

The table presents the Out-of-sample mean squared error (MSE) expressed in basis points for 30 stocks in DAX30 for May 2011. Note that the mean of the EWS changes is around zero and the standard deviation is around one. The average real time for 1 tick is around 7 seconds.

Table 12: Economic Value of the Model

Ticker	Aggregation of 10 ticks			Aggregation of 20 ticks			Aggregation of 30 ticks			Aggregation of 40 ticks			Aggregation of 50 ticks		
	Gains1	Gains2	#_nb	Gains1	Gains2	#_nb	Gains1	Gains2	#_nb	Gains1	Gains2	#_nb	Gains1	Gains2	#_nb
ADS	21.51%	-1.26%	292	22.17%	3.00%	145	18.86%	1.42%	97.00	20.12%	1.73%	72	21.56%	13.00%	58
ALV	1.66%	-17.48%	713	2.32%	-19.77%	356	-11.12%	-28.52%	237.00	-3.37%	-27.34%	178	-8.27%	-28.37%	142
BAS	6.36%	-21.99%	816	0.82%	-24.65%	408	8.90%	-13.58%	272.00	8.20%	-15.79%	204	-0.09%	-20.48%	163
BAYN	14.21%	-14.42%	490	18.88%	-7.79%	245	20.83%	-6.10%	163.00	12.56%	-9.55%	122	11.29%	-4.95%	97
BEI	14.51%	4.22%	204	19.38%	10.36%	102	17.21%	11.14%	68.00	21.93%	17.75%	51	22.95%	19.13%	40
BMW	9.08%	-10.51%	609	10.40%	-8.34%	304	19.04%	0.95%	202.00	15.47%	-2.69%	152	18.04%	-0.67%	121
CBK	20.67%	8.89%	1020	24.20%	16.27%	509	23.68%	18.49%	339.00	24.40%	17.56%	254	20.93%	15.11%	203
DAI	9.01%	-10.18%	803	13.29%	-1.91%	401	8.19%	-3.85%	267.00	9.52%	-2.51%	200	15.18%	6.06%	160
DB1	22.80%	-1.40%	450	25.87%	0.92%	224	18.39%	2.36%	149.00	23.87%	3.41%	112	24.48%	8.28%	89
DBK	23.53%	-3.20%	894	20.09%	-3.45%	447	23.30%	0.65%	297.00	15.46%	-5.28%	223	25.57%	1.93%	178
DPW	18.50%	2.94%	293	20.54%	6.06%	146	15.15%	8.26%	97.00	19.90%	4.33%	73	21.16%	8.65%	58
DTE	10.80%	1.19%	401	12.94%	3.18%	200	12.37%	4.06%	133.00	14.86%	6.17%	100	10.12%	6.60%	80
EOAN	13.02%	-0.37%	537	18.06%	7.06%	268	15.64%	8.05%	179.00	11.03%	7.44%	134	9.31%	7.84%	107
FME	9.68%	-1.48%	292	13.01%	0.38%	146	8.53%	-4.03%	97.00	15.89%	1.77%	72	7.26%	-2.27%	58
FRE	19.98%	-4.36%	302	15.99%	-2.39%	151	22.52%	5.88%	100.00	19.26%	-4.96%	75	22.65%	7.48%	60
HEI	23.61%	-2.57%	460	27.16%	4.69%	230	21.80%	3.22%	153.00	23.87%	4.61%	114	19.36%	-0.43%	91
HEN3	19.45%	11.18%	303	20.25%	13.73%	151	25.11%	20.22%	101.00	24.56%	22.26%	75	27.40%	22.47%	60
IFX	18.20%	6.59%	534	18.60%	12.93%	267	21.51%	11.55%	178.00	24.69%	17.27%	133	18.46%	9.56%	106
LHA	14.77%	-8.80%	312	22.80%	2.51%	156	22.46%	0.05%	104.00	20.09%	5.59%	78	15.38%	1.69%	62
LIN	12.40%	-1.45%	196	14.78%	-0.46%	98	15.71%	1.75%	65.00	17.45%	2.96%	48	8.74%	1.65%	39
MAN	13.60%	4.11%	421	18.95%	12.09%	210	26.41%	18.03%	140.00	14.76%	14.52%	105	25.02%	20.44%	84
MEO	27.58%	9.38%	299	33.26%	22.82%	149	36.47%	22.17%	99.00	30.92%	17.89%	74	33.49%	21.85%	59
MRK	21.31%	-3.57%	299	24.85%	0.39%	149	26.42%	-1.04%	99.00	34.23%	5.20%	74	36.79%	6.51%	59
MUV2	7.06%	-1.88%	239	12.34%	0.24%	119	11.90%	0.03%	79.00	12.55%	0.61%	59	8.03%	2.17%	47
RWE	26.79%	-3.23%	477	18.97%	-1.87%	238	18.18%	-1.94%	159.00	20.46%	1.98%	119	13.70%	-2.06%	95
SAP	12.89%	-4.40%	622	17.82%	3.20%	311	14.42%	4.27%	207.00	16.54%	3.62%	155	14.25%	4.53%	124
SDF	18.60%	3.81%	354	24.01%	7.33%	177	21.40%	9.52%	118.00	28.43%	17.89%	88	27.81%	19.14%	70
SIE	15.21%	-2.38%	872	14.89%	0.26%	436	20.34%	7.64%	290.00	17.70%	3.23%	217	21.75%	6.46%	174
TKA	15.21%	-7.98%	547	21.38%	-0.67%	273	23.04%	0.62%	182.00	20.85%	2.94%	136	18.15%	-1.73%	109
VOW3	23.06%	0.69%	361	20.79%	3.54%	180	16.66%	2.87%	120.00	18.93%	2.18%	90	11.80%	2.56%	72
Mean	16.17%	-2.33%	480	18.29%	1.99%	240	18.11%	3.47%	159.70	18.50%	3.83%	120	17.41%	5.07%	96
Median	15.21%	-1.68%	435.5	18.96%	1.72%	217	18.95%	2.62%	144.50	19.09%	3.32%	108.5	18.31%	6.26%	86.5
Min	1.66%	-21.99%	196	0.82%	-24.65%	98	-11.12%	-28.52%	65.00	-3.37%	-27.34%	48	-8.27%	-28.37%	39
Max	27.58%	11.18%	1020	33.26%	22.82%	509	36.47%	22.17%	339.00	34.23%	22.26%	254	36.79%	22.47%	203
p-value	$<$0.001	0.104		$<$0.001	0.263		$<$0.001	0.068		$<$0.001	0.057		$<$0.001	0.018	

The table compares the order execution performance of the decomposition strategy with that of uniform (Gains 1) and moving average (Gains 2) strategies for 30 stocks in DAX30 during the third week of May 2011. Gains 1 and 2 are the average gains in spread per transaction expressed in percentage, and #_nb is the number of trade during one week out-of-sample. The p-value is for the one-sample t-test which examines whether the model-based strategy dominates the uniform or moving average strategies. The strategies are applied to aggregated intervals of various ticks. The average real time for 1 tick is around 7 seconds.

Table 13: Empirical and Simulated Time-Based Resilience

Ticker	1-BPS Shock		2-BPS Shock		3-BPS Shock		4-BPS Shock		5-BPS Shock	
	Empir.	Sim.	Empir.	Sim.	Empir.	Sim.	Empir.	Sim.	Empir.	Sim.
ADS	11	14	17	22	23	31	27	39	32	46
ALV	10	19	19	31	37	42	20	52	23	61
BAS	10	9	20	16	35	23	39	30	52	36
BAYN	18	10	29	19	45	26	55	35	71	43
BEI	8	10	12	17	17	23	21	29	25	35
BMW	10	11	20	19	28	27	36	34	44	41
CBK	11	12	16	20	21	27	27	33	33	39
DAI	10	10	18	17	25	24	35	31	42	37
DB1	12	17	19	26	27	36	34	45	34	52
DBK	14	10	29	18	42	25	43	32	44	39
DPW	9	11	14	18	19	25	28	31	30	38
DTE	9	11	15	20	18	27	23	35	30	42
EOAN	8	9	14	16	20	23	22	30	32	37
FME	10	17	16	27	22	37	27	43	32	51
FRE	12	16	15	24	19	33	23	40	30	47
HEI	10	19	17	30	26	40	34	48	39	56
HEN3	13	16	20	25	28	35	35	44	39	51
IFX	9	12	15	19	21	26	25	33	29	40
LHA	10	11	15	17	20	23	25	30	35	35
LIN	7	8	10	13	12	18	14	23	18	28
MAN	21	23	33	36	47	48	61	58	69	66
MEO	14	13	21	21	26	29	31	37	27	44
MRK	14	14	23	22	32	30	43	37	53	44
MUV2	5	8	8	13	16	18	28	23	28	28
RWE	14	16	25	26	36	35	42	44	49	53
SAP	20	10	34	19	53	27	87	35	121	43
SDF	10	13	15	21	20	28	26	36	29	43
SIE	20	10	28	18	39	26	56	34	57	41
TKA	13	13	21	20	32	28	40	34	44	41
VOW3	10	8	14	13	18	17	23	22	28	26
Mean	11.7	12.6	19.0	20.8	27.5	28.6	34.4	35.9	40.7	42.8
Median	10	12	17	19	25	27	30	35	34	42
Min	5	8	8	13	12	17	14	22	18	26
Max	21	23	34	36	53	48	87	58	121	66

The table presents the empirical and simulated time-based resilience, measured in ticks, of the higher-level of the LOB for the 30 stocks in DAX during May 2011. The empirical time-based resilience is measured by the number of ticks with which liquidity reverts to its reference state from a given liquidity shock. The simulated time-based resilience is the average of reversion time for all simulated paths. The average real time for 1 tick is around 7 seconds.

Table 14: Empirical and Simulated Probability-Based Resilience

	1-BPS Shock						3-BPS Shock					
	5 tick		10 tick		30 ticks		5 tick		10 ticks		30 ticks	
Ticker	Empir.	Sim.	Empir.	Sim.	Empir.	Sim.	Empir.	Sim.	Empir.	Sim.	Empir.	Sim.
ADS	50.57%	46.38%	69.38%	56.50%	92.03%	71.92%	20.71%	8.24%	39.69%	21.68%	74.96%	51.70%
ALV	37.36%	36.54%	49.72%	44.94%	63.27%	56.80%	1.84%	4.44%	3.76%	11.92%	9.29%	32.92%
BAS	52.58%	54.44%	71.82%	67.44%	93.14%	85.86%	17.54%	11.28%	32.08%	29.80%	67.24%	69.46%
BAYN	37.81%	50.36%	54.94%	62.78%	82.55%	80.66%	10.40%	7.52%	21.62%	22.96%	51.33%	60.04%
BEI	57.00%	52.68%	75.44%	62.94%	95.94%	78.56%	26.56%	15.22%	48.76%	32.82%	84.57%	63.50%
BMW	54.48%	52.02%	72.82%	61.96%	93.35%	78.38%	16.97%	11.06%	33.97%	26.64%	71.33%	59.54%
CBK	51.34%	49.64%	69.74%	57.46%	91.56%	69.38%	21.46%	15.68%	40.70%	30.68%	78.88%	54.36%
DAI	54.80%	52.60%	73.62%	64.52%	93.50%	80.68%	17.85%	11.32%	33.42%	29.10%	71.55%	63.68%
DB1	50.20%	42.08%	69.56%	52.56%	92.11%	66.70%	20.43%	7.06%	37.34%	17.38%	73.54%	43.78%
DBK	48.05%	51.66%	66.06%	62.94%	88.60%	79.40%	12.95%	11.56%	25.41%	28.02%	58.21%	61.98%
DPW	52.21%	51.78%	73.02%	62.06%	94.79%	77.16%	25.88%	15.18%	45.94%	31.14%	84.47%	61.48%
DTE	51.28%	50.72%	72.29%	62.36%	95.50%	80.14%	26.13%	9.52%	48.65%	24.82%	82.66%	60.22%
EOAN	61.52%	53.30%	79.14%	67.04%	95.49%	86.34%	19.40%	9.12%	39.02%	25.62%	79.60%	69.00%
FME	54.87%	41.94%	72.51%	47.52%	93.22%	54.92%	20.02%	7.96%	39.15%	18.68%	76.25%	36.58%
FRE	45.81%	45.44%	64.93%	52.50%	91.27%	64.38%	21.33%	12.08%	41.24%	24.34%	82.07%	47.40%
HEI	52.14%	39.06%	70.83%	47.54%	93.21%	59.10%	20.72%	6.66%	38.26%	15.80%	74.79%	37.06%
HEN3	48.35%	43.50%	65.07%	54.24%	89.08%	66.62%	15.46%	7.92%	31.47%	18.42%	68.60%	46.16%
IFX	55.85%	51.68%	74.51%	60.56%	95.08%	75.40%	21.37%	14.60%	41.32%	30.56%	80.20%	59.20%
LHA	51.89%	52.54%	70.96%	61.58%	93.48%	74.28%	22.03%	18.70%	41.15%	35.60%	80.04%	61.64%
LIN	61.87%	60.70%	81.48%	69.44%	97.41%	85.24%	36.63%	23.22%	60.86%	44.26%	92.95%	74.52%
MAN	37.50%	31.22%	53.64%	42.02%	79.56%	53.38%	11.36%	3.60%	23.22%	8.72%	52.93%	27.04%
MEO	44.17%	48.88%	62.07%	58.02%	87.33%	72.74%	17.18%	10.58%	34.02%	24.86%	70.88%	54.28%
MRK	47.39%	46.82%	63.56%	54.06%	87.31%	65.82%	15.90%	12.88%	32.70%	25.54%	67.99%	50.20%
MUV2	71.87%	59.94%	89.46%	70.36%	98.88%	86.54%	34.58%	18.64%	54.91%	40.18%	84.58%	75.62%
RWE	44.82%	46.10%	62.66%	54.40%	87.73%	68.48%	11.86%	11.12%	23.51%	19.78%	54.75%	45.60%
SAP	36.36%	48.26%	53.67%	60.48%	80.75%	79.24%	9.25%	7.02%	18.97%	21.58%	47.93%	57.76%
SDF	50.63%	49.80%	69.14%	58.90%	92.88%	72.96%	20.19%	12.26%	39.29%	26.42%	78.43%	55.64%
SIE	30.69%	50.38%	47.65%	63.24%	79.86%	81.88%	11.71%	9.02%	24.01%	24.90%	55.82%	61.90%
TKA	48.79%	50.02%	67.11%	59.60%	90.15%	73.34%	16.52%	13.60%	33.54%	29.78%	68.72%	57.06%
VOW3	51.65%	59.02%	70.87%	71.08%	93.32%	86.62%	23.51%	25.54%	44.13%	45.74%	82.61%	77.08%
Mean	49.79%	48.98%	67.92%	59.03%	90.08%	73.76%	18.92%	11.75%	35.74%	26.26%	70.24%	55.88%
Median	50.96%	50.19%	69.65%	60.52%	92.50%	74.84%	19.71%	11.20%	37.80%	25.58%	74.17%	58.48%
Min	30.69%	31.22%	47.65%	42.02%	63.27%	53.38%	1.84%	3.60%	3.76%	8.72%	9.29%	27.04%
Max	71.87%	60.70%	89.46%	71.08%	98.88%	86.62%	36.63%	25.54%	60.86%	45.74%	92.95%	77.08%

The table presents the empirical and probability-based resilience of the higher-level of the LOB for the 30 stocks in DAX during May 2011. We first classify liquidity shocks according to their magnitude and calculate reversion time for all shocks with the same magnitude. Therefore, for a given magnitude of liquidity shock, we have a sample of reversion times. The empirical probability-based resilience is the value of the empirical cumulative distribution function evaluated at a given number of ticks. The simulated probability-based resilience is the number of paths where the spread reverts to its initial state for a given tick.

Online Appendix for

"The Dynamics of Ex-ante Weighted Spread: An Empirical Analysis"

Georges Dionne   Xiaozhou Zhou

Abstract

This appendix contains three sections. Section I provides further details on the reconstruction of the LOB. Section II shows the estimation results for the trade duration factor, and Section III presents the estimation results for the quote duration factor. Also, this appendix shows the intraday seasonality of trade and quote durations for all stocks in DAX30 for May 2011.

I. Reconstruction of the LOB

The reconstruction of the LOB is predominantly based on two main types of data streams: delta and snapshot. The delta tracks all the possible updates in the LOB such as entry, revision, cancellation and expiration, whereas the snapshot gives an overview of the state of the LOB and is sent after a constant time interval for a given stock. Xetra original data with delta and snapshot messages are first processed using the XetraParser algorithm, developed by Bilodeau (2013) in order to make Deutsche Börse Xetra raw data usable for academic and professional analysts. XetraParser reconstructs the real-time order book sequence including all the information for both auctions and continuous trading by implementing the Xetra trading protocol and Enhanced Broadcast. We then put the raw LOB information in order and in a readable format for each update time. We also retrieve useful and accurate information about the state of the LOB and the precise timestamp for order modifications and transactions during continuous trading.

II. Trade Duration Factor

It is well known that high-frequency duration data is characterized by seasonality. Before modeling the trade durations, we remove seasonality under a multiplicative form proposed by Anatolyev and Shakin (2007)[1] and apply the model to the deseasonalized data. Figure A.1 illustrates the evolution of the seasonality factors for trade durations.

[Insert Figure A.1 here]

Table A.2 presents the estimated results of the lagged dependent variables for all the stocks in the sample. The ACD-related models are based on the ARMA structure, meaning that the determinant parts of the dynamics of durations are specified by the lagged duration and lagged error term. As we expected, the trade durations of all stocks are highly autocorrelated. Taking the models' efficiency and parsimony into consideration, the number of lagged trade durations varies from one to three. The sum of the coefficients of lagged trade durations for all stocks is around 0.9, which confirms a very high degree of persistence in autocorrelation. Regarding the error terms for all stocks, the means of $Gamma1$ and $Gamma2$ are 0.53 and 1.15, respectively,

[1] We obtain the deseasonalized durations by dividing the raw trade durations by expected trade durations, which are the interpolation value from the thirty-minute average trade durations.

indicating that the distribution of the random part is abrupt and near zero; that is, expected trade duration shocks are very small.

[Insert Table A.2 here]

Considering the market-related variables mentioned above, we put four such variables in the trade duration equations: *DeltaSpread, AveSpread, SquareRoot (vol),* and *Abs(sign.vol).* Consistent with Engle and Lunde (2003), we have a positive and significant coefficient for *DeltaSpread*. Intuitively, when the stocks become less liquid, traders will slow their trading intensities, and trading durations will become longer. Contrary to Engle and Lunde (2003), we find a positive sign for *AveSpread* coefficient for most stocks. That is, the higher the *AveSpread*, the longer the trade durations. The difference between *DeltaSpread* and *AveSpread* is that the former captures the short-run spread change and the latter relates to the long-term spread change. This result reveals that trade intensity is sensitive for both short-run and long-run spread change. When the stocks become less liquid, traders slow down their activities and then wait until liquidity increases.

Another important market-related variable is volume-related. For all stocks, the coefficients of $SquareRoot\,(vol)$ are all negative and significant at the 1% level. This means that large trades will generate higher trading intensity and shorter trade durations. According to Easley and O'Hara (1987), large trades are likely to be related to information trade because informed traders try to exploit their information advantage by increasing both the trading intensity and trading quantity. Another volume-related variable is $Abs(sign.vol)$ which measures the volume imbalance (in shares) of the last ten trades (a higher value means a higher level of imbalance and a zero value means a completely balanced trading activity). Most stocks have small positive coefficients at the 1% level. The measure of imbalance also relates to information trading. Our results suggest that when the trades become imbalanced, the trade intensity will decrease. Presumably, when the non-informed traders observe an imbalanced trading history, they will slow down their trading activity to protect themselves.

III. Quote Duration Factor

As for trade durations, quote durations also feature diurnal seasonality. Figure A.2 presents the evolution of the seasonality factors for quote durations. Table A.4 reports the estimated results of lagged dependent variables for all stocks. Similar to trade durations, quote durations are also highly persistent. The number of lagged values varies from two to six. Comparing the Log-ACD model with the traditional ARMA structure, the sum of the coefficient of the "AR" part in the quote duration equation is around 0.6. The relatively small coefficients can be explained by the fact that the start point of our quote duration is the trade timestamp. When there is more than one update between two trades, only the first one is used to calculate the quote duration. This sampling "deletes" some autocorrelation in quote durations. Regarding the coefficients of the error term, the estimated coefficients vary from 0.007 to 0.144, confirming the sampling effect in autocorrelation.

[Insert Figure A.2 here]

[Insert Table A.4 here]

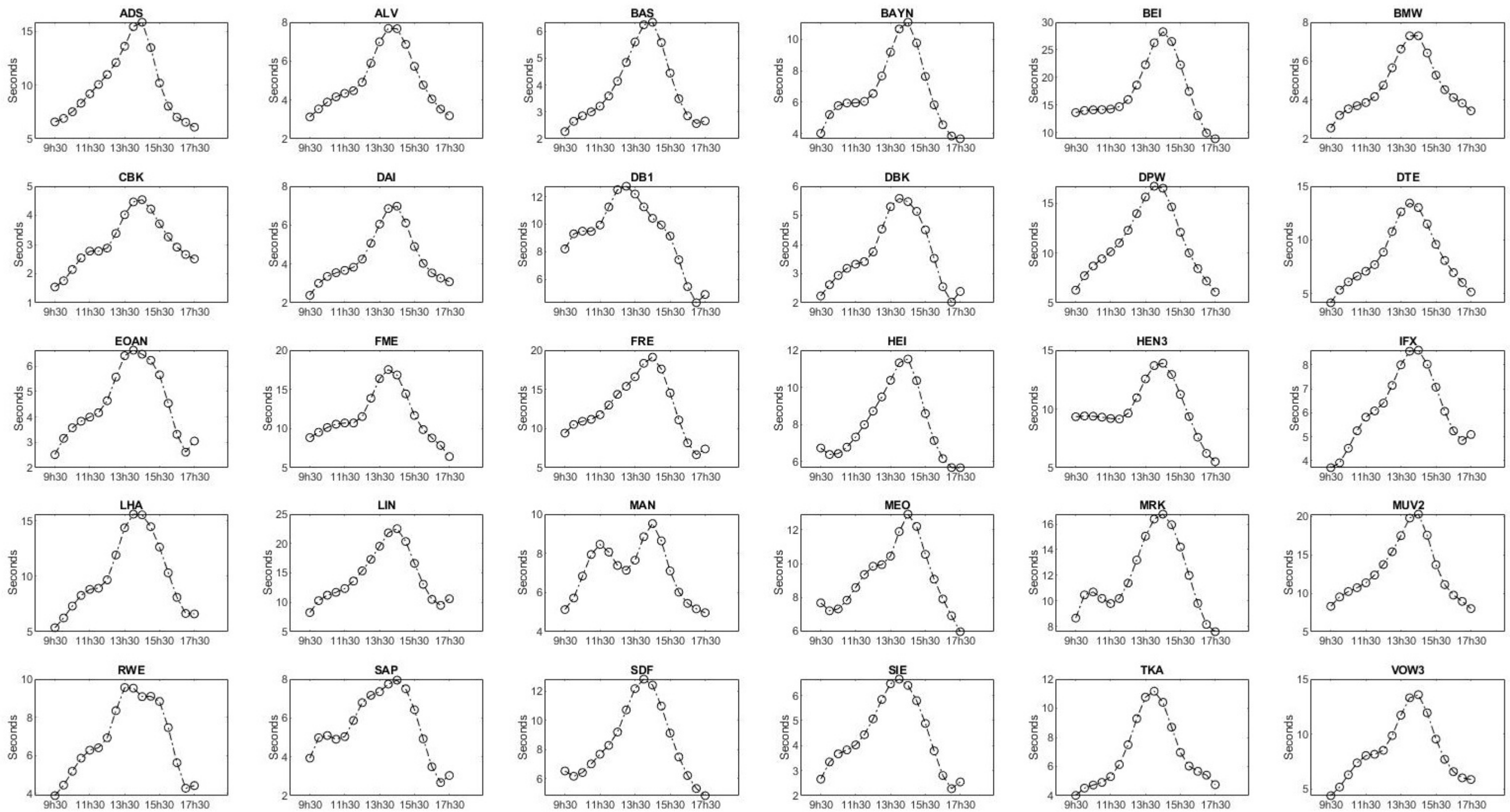
The censored effect is captured by the product of the censored dummy variable and the lagged error term. The censored effect is positive and significant at the 1% level for 27 stocks. The implication is that if the last quote duration is censored, the next quote duration is likely to be longer and censored again. Trade duration-related variables consist of the current error term, lagged error term and lagged expected trade duration. The estimated results show that the current error term and expected trade duration have a positive and significant effect on the quote durations. This suggests that when the (current and lagged) trade duration innovations and expected trade durations are high, the quote duration will lengthen. Intuitively, as quote activity adjusts to trade activity, trade duration and quote duration are correlated positively.

$AveSpread$ has a negative impact on the quote durations, which is the opposite of the trade duration. The coefficients are negative and significant at the 1% level for all stocks. Spread variables are very important in explaining the trade activity and quote activity. This suggests that when the average spread is large, market order traders and LOB traders react differently. Market order traders slow down their trading speed when observing an increasing spread, whereas LOB traders speed up to update their price or quantity of limit orders. For an intraday LOB trader, a major concern is adverse selection. By attentively monitoring the change in spread, LOB traders attempt to avoid this risk by updating their quote rapidly. For 22 stocks over 30, $DeltaSpread$ has a positive impact on the quote duration, suggesting that a short-term increase in spread will reduce the quoting intensity.

The effects of the volume-related variables, $SquareRoot\,(vol)$ and $Abs(sign.vol)$, on quote duration are both negative. More specifically, large trades predict shorter quote durations. As mentioned above, large trades relate to informed trades. Informed traders exploit short-lived information by increasing trade intensity and trade quantity. When trades become more intensive, so do quote revisions. As a result, the quote durations shorten. The negative effect of $Abs(sign.vol)$ on quote duration suggest that $Abs(sign.vol)$ is more likely to be a proxy for liquidity shock than information asymmetry. When there is a need for liquidity, liquidity providers compete to provide liquidity and reduce the quote durations.

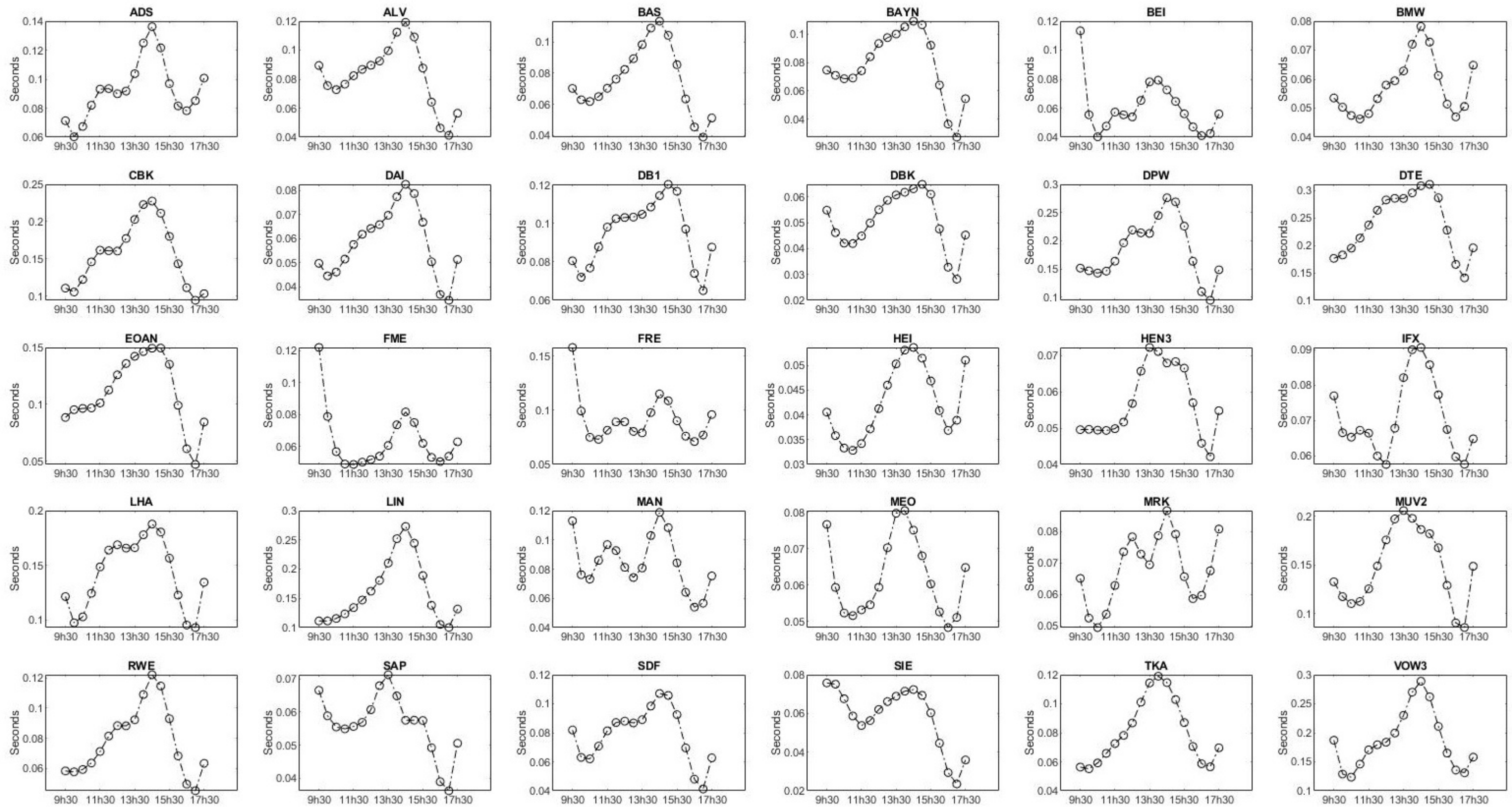
The *BackQuote duration* has a positive and significant impact on the following quote duration. A longer *BackQuote duration* can be either a low trade intensity or a high quote intensity. That is, a long trade duration or a short quote duration. Moreover, a long trade duration implies a long quote duration. The estimated results suggest that the long trade duration effect dominates the short quote duration effect. Concerning the effect of the EWS, it is negative and significant at the 1% level for 22 stocks. 8 stocks have a positive significant sign. Theoretically, there are arguments to support either sign. A high EWS reveals a more risky situation, especially a high adverse selection risk. LOB traders speed up their quote revisions to reduce this kind of risk. This is more pronounced for less liquid stocks. In contrast, the increase in the EWS will slow down the trade activity and then the quote activity.

Figure A.1: Intraday Seasonality Pattern for Trade Durations



This figure presents the intraday patterns of seasonality variables for trade durations of all stocks in DAX30 for the period of May 2011. We first compute the thirty-minute average trade durations for each day in the sample and then use cubic splines to smooth the seasonal factor.

Figure A.2: Intraday Seasonality Pattern for Quote Durations



This figure presents the intraday patterns of seasonality variables for quote durations of all stocks in DAX30 for the period of May 2011. We first compute the thirty-minute average quote durations for each day in the sample and then use cubic splines to smooth the seasonal factor.

Table A.1: Ljung-Box Statistics for Trade Durations, Quote Durations, Activity, Direction and Size Factor of EWS^{High}

	Deseasonalized Trade Duration			Deseasonalized Quote Duration			Activity			Direction			Size		
Ticker	LB(5)	LB(10)	LB(15)	LB(5)	LB(10)	LB(15)	LB(5)	LB(10)	LB(15)	LB(5)	LB(10)	LB(15)	LB(5)	LB(10)	LB(15)
ADS	3061.47	4653.86	5876.46	446.51	602.63	745.88	2636.25	3419.22	3844.23	4315.61	4326.76	4331.99	12177.21	17073.94	20103.96
ALV	9989.79	14186.84	17356.09	5119.40	7006.65	8235.35	11272.07	13000.21	13981.99	15875.38	15889.92	15899.44	20700.60	26333.55	30698.30
BAS	16217.08	24405.82	30885.76	3163.69	4209.56	5210.03	4579.38	5363.55	5760.86	16036.31	16062.61	16066.44	14961.36	20086.41	23474.36
BAYN	8879.53	12838.34	15630.98	2147.68	2706.74	3195.50	2143.88	2552.94	2811.50	11454.47	11468.28	11473.04	10931.18	15083.72	18168.56
BEI	1724.89	2342.90	2681.06	211.24	407.16	419.68	1041.86	1324.81	1445.95	2420.43	2430.32	2431.69	5668.29	7336.44	8637.62
BMW	10276.26	15342.18	19208.61	1595.90	2165.36	2611.50	4119.62	4653.13	4998.09	12424.47	12445.17	12456.35	15128.27	19639.66	23313.17
CBK	40070.34	66220.24	88024.34	2409.20	3278.89	3994.85	20031.43	24004.38	26136.10	15293.30	15317.10	15327.22	42915.62	58225.90	68261.91
DAI	11279.05	16684.82	20284.30	233.39	303.72	338.10	4966.47	5954.74	6594.66	15506.09	15517.58	15523.31	21660.26	29334.21	35262.64
DB1	7972.18	12591.04	16202.61	789.73	990.56	1102.75	3668.81	4889.83	5681.53	5556.86	5564.99	5570.37	18692.98	27196.07	34118.12
DBK	14307.39	20432.41	25029.75	3912.86	4782.32	5440.99	7601.46	8983.19	9793.76	18404.23	18423.37	18429.42	28863.36	38763.92	47237.64
DPW	6178.22	8927.76	11019.40	1365.49	1606.67	1859.83	6453.58	7375.46	7803.30	5750.92	5758.41	5763.36	7697.12	10060.27	11372.64
DTE	7106.92	9445.06	11025.44	3720.43	4865.17	5643.76	16661.48	19319.36	21096.03	8016.71	8027.16	8033.88	15080.89	19165.94	22152.61
EOAN	14111.17	21355.13	27117.89	4197.19	5648.84	6573.72	15343.06	19534.62	22376.09	19559.62	19571.88	19575.72	35712.61	50836.94	62827.13
FME	2699.35	3905.69	4879.51	151.98	265.78	321.17	1648.76	2212.26	2515.99	4023.56	4033.07	4037.26	14078.82	20426.04	24603.35
FRE	2205.36	2982.55	3621.83	275.13	380.58	434.44	1838.18	2331.00	2628.08	2843.87	2856.07	2864.36	13741.20	19117.86	22925.92
HEI	3150.11	4803.43	5900.35	599.09	791.80	873.87	3937.28	5020.18	5736.37	5286.13	5306.07	5322.78	16737.33	24487.31	29340.47
HEN3	3535.01	5079.80	6358.75	633.72	707.28	828.31	2286.22	2846.46	3206.97	4684.10	4704.39	4709.99	14377.07	20421.28	24757.39
IFX	9363.19	13739.72	17008.88	1262.42	1641.81	1736.90	4107.84	4726.74	5065.93	6873.96	6901.87	6903.54	14408.56	18969.73	22340.86
LHA	5809.41	8127.39	9890.05	904.76	1101.43	1301.89	4901.61	5529.19	5827.92	4647.21	4656.10	4661.54	9414.05	13393.22	15993.87
LIN	1476.28	2242.36	2854.79	557.57	701.72	782.75	4826.22	5692.29	6139.43	4322.34	4324.17	4328.62	6730.86	8739.22	9751.24
MAN	10188.13	15418.24	19551.38	315.54	418.32	465.05	5605.40	7201.35	8326.19	6896.03	6927.53	6935.80	25727.66	39752.81	51393.46
MEO	3111.22	4813.34	6064.38	502.99	558.96	623.57	2804.49	3335.78	3709.03	5574.63	5595.66	5600.50	10080.16	13408.18	15572.17
MRK	2848.60	4228.15	5573.69	742.85	863.89	1136.15	1742.86	2125.24	2356.69	4082.69	4097.51	4102.76	12961.70	17700.22	21967.60
MUV2	3033.17	4254.26	5164.51	1109.54	1590.97	1766.54	5815.79	6547.67	6862.33	6629.64	6632.58	6635.83	5766.94	7136.69	7879.07
RWE	7379.14	10637.18	12829.14	1795.02	2636.88	3290.24	4015.56	4752.18	5158.72	10486.48	10504.80	10523.15	15182.51	22013.77	27693.48
SAP	9552.91	14211.18	17890.10	1503.36	2130.82	2508.38	3995.94	4646.68	5144.27	13667.89	13687.54	13692.66	13075.66	16646.90	19568.38
SDF	4450.22	6547.83	8576.12	595.59	794.91	889.38	2503.85	2992.30	3165.23	5704.06	5710.09	5715.96	14711.03	21313.28	25586.27
SIE	12829.93	19518.87	24722.10	1508.66	1990.77	2254.23	4028.74	4595.22	4822.91	16985.26	17000.47	17001.24	17659.17	23222.70	27427.12
TKA	9415.97	14832.17	19490.85	925.77	1334.14	1463.24	3359.30	3867.52	4242.27	7288.83	7315.39	7322.61	17828.52	24817.37	29717.80
VOW3	8259.60	12276.83	15081.99	962.61	1206.22	1461.18	8679.75	9739.79	10340.44	5997.01	6003.93	6006.12	11138.95	14719.17	17249.12

The table reports the Ljung-Box statistic on deseasonalized trade duration, deseasonalized quote duration, activity, direction and size factors of the EWS^{High} for different stocks at 5, 10 and 15 lags . The critical value for LB(5), LB(10), and LB(15), are 11.07, 18.30 and 24.99, respectively.

Table A.2: Estimation Results for Trade Durations

	Autoregressive Part						Market-related variables						
	β_1	β_2	β_3	α_1	α_2	α_3	$gamma1$	$gamma2$	Const.	Del.Spread	Ave.Spread	Sqrt(Vol)	Abs(sign.vol)
ADS	0.886***	-0.070***	0.124***	0.120***			0.362***	1.277***	0.083***	23.935***	0.522***	-0.2258***	0.028***
ALV	1.192***	-0.098**	-0.107***	0.145***		-0.043***	0.854***	0.352***	-0.029***	13.500***	0.246***	-0.0206***	0.004***
BAS	0.974***	0.020	-0.020*	0.148***		-0.036***	0.603***	0.641***	-0.019***	30.863***	0.193***	-0.0567***	0.008***
BAYN	0.655***	0.089***	0.087***	0.208***			0.662***	0.561***	0.154***	13.748***	0.286*	-0.3888***	-0.015
BEI	1.216***	-0.202***	-0.021	0.269***	-0.198***		0.130***	5.741***	0.095***	12.415***	-0.453***	-0.0813***	0.000
BMW	0.874***	-0.047***	0.036***	0.126***			0.342***	1.380***	0.117***	28.111***	0.745***	-0.2907***	0.015***
CBK	0.842***	-0.013	0.110***	0.118***			0.739***	0.529***	-0.006	11.419***	0.144***	-0.1307***	-0.003
DAI	0.867***	-0.036	0.081***	0.124***			0.675***	0.541***	-0.005	20.024***	1.250***	-0.1752***	0.001
DB1	0.943***	-0.081**	0.119***	0.103***			0.536***	0.709***	-0.025***	14.334***	-0.218***	-0.0583***	0.014***
DBK	1.015***	-0.130***	0.091***	0.198***	-0.065***	-0.043***	0.356***	1.234***	0.006	34.775***	0.028	-0.0882***	0.000
DPW	0.934***	-0.026	0.005	0.132***			0.739***	0.397***	-0.015	15.890***	0.977***	-0.2039***	0.012***
DTE	0.860***	-0.080**	0.098***	0.162***			1.030***	0.311***	-0.037***	9.025***	0.800***	-0.1756***	-0.001
EOAN	1.155***	-0.071**	-0.093***	0.151***	-0.062***	-0.041***	0.776***	0.487***	-0.038***	20.673***	0.181***	-0.0160***	0.002***
FME	0.838***	0.017	0.053***	0.128***			0.309***	1.540***	0.181***	20.566***	0.346***	-0.3102***	0.015***
FRE	0.869***	-0.058*	0.114***	0.121***			0.276***	1.760***	0.143***	19.642***	0.134	-0.2303***	0.015***
HEI	0.782***	-0.036*	0.092***	0.143***			0.187***	3.559***	0.345***	20.128***	0.337***	-0.4644***	0.015***
HEN3	0.795***	0.028	-0.018	0.116***			0.273***	1.902***	0.168***	22.524***	0.804***	-0.3628***	0.015***
IFX	0.873***	-0.073***	0.077***	0.124***			0.445***	0.924***	0.006	21.680***	1.063***	-0.2321***	0.013***
LHA	0.905***	-0.043	0.052***	0.114***			0.526***	0.647***	0.061***	18.150***	0.239***	-0.2062***	0.017***
LIN	0.970***	-0.018	-0.001	0.095***			0.752***	0.397***	0.020*	13.817***	0.254***	-0.1309***	0.015***
MAN	1.084***	-0.352***	0.206***	0.111***			0.334***	1.429***	0.111***	13.221***	0.200***	-0.2379***	0.006***
MEO	0.962***	-0.100***	0.077***	0.073***			0.265***	1.918***	0.017*	32.199***	0.263***	-0.1008***	0.015***
MRK	0.679***	0.142***	0.045**	0.145***			0.433***	0.900***	0.219***	14.177***	0.644***	-0.3879***	0.012**
MUV2	0.874***	-0.051	0.039	0.137***			0.792***	0.361***	0.056***	12.231***	0.894***	-0.2818***	-0.002
RWE	1.094***	-0.064**	-0.049***	0.155***		-0.032***	0.732***	0.479***	-0.029***	26.830***	0.116***	-0.0400***	-0.001
SAP	0.874***	-0.009	0.077***	0.142***			0.560***	0.671***	0.031***	23.782***	0.215**	-0.1747***	0.005**
SDF	0.750***	-0.050**	0.120***	0.132***			0.239***	2.193***	0.306***	20.189***	0.651***	-0.4783***	0.006
SIE	0.978***	-0.028	0.009	0.155***		-0.019***	0.788***	0.459***	0.042***	26.343***	0.242***	-0.1502***	0.009***
TKA	0.934***	-0.073***	0.070***	0.112***			0.507***	0.721***	0.044***	21.356***	0.534***	-0.2049***	0.007***
VOW3	0.920***	-0.101***	0.099***	0.133***			0.668***	0.515***	0.017**	11.161***	-0.085***	-0.1771***	-0.011***
Mean	$\sum \beta_j$: 0.918			$\sum \alpha_j$: 0.113			0.530	1.151	0.067	19.557	0.385	-0.203	0.007
Median	$\sum \beta_j$: 0.928			$\sum \alpha_j$: 0.119			0.531	0.690	0.036	20.076	0.259	-0.191	0.008
Min	$\sum \beta_j$: 0.805			$\sum \alpha_j$: 0.040			0.130	0.311	-0.038	9.025	-0.453	-0.478	-0.015
Max	$\sum \beta_j$: 0.993			$\sum \alpha_j$: 0.208			1.030	5.741	0.345	34.775	1.250	-0.016	0.028

The table reports the estimated results for deseasonalized trade durations and the distribution of the estimated parameters. β and α are parameters for the logACD model: $\psi_k = \exp\left(\omega + \sum_{j=1}^{p} \alpha_j \varepsilon_{k-j} + \sum_{j=1}^{l} \beta_j \ln \psi_{k-j} + \Psi' W_{k-1}\right)$, and market-related variables include variables capturing volume and liquidity of the market. ***, ** and * denote either coefficient estimates that are significantly different from zero or test statistics that are significant at the 1%, 5% and 10%, respectively.

Table A.3: Ljung-boxtest for Trade duration

Ticker	LB(5)	LB(10)	LB(15)
ADS	13.62	28.07	35.66
ALV	36.02	56.36	81.30
BAS	27.28	41.91	54.51
BAYN	20.89	49.85	88.41
BEI	18.71	28.22	30.53
BMW	39.65	44.58	85.01
CBK	19.47	40.10	48.99
DAI	57.26	76.42	85.18
DB1	12.98	35.01	58.23
DBK	61.92	83.80	110.87
DPW	34.53	54.19	65.26
DTE	14.19	20.05	36.39
EOAN	22.10	42.32	60.94
FME	10.18	19.66	24.22
FRE	7.39	12.45	22.85
HEI	4.59	13.04	20.72
HEN3	17.48	24.39	61.58
IFX	39.38	52.08	59.89
LHA	35.35	63.98	69.99
LIN	34.32	40.45	48.61
MAN	23.99	27.97	34.30
MEO	46.62	61.52	75.81
MRK	7.61	11.37	18.31
MUV2	27.59	44.73	54.15
RWE	17.87	28.98	38.89
SAP	38.93	66.36	70.73
SDF	1.92	3.37	11.02
SIE	14.24	48.84	59.89
TKA	61.36	83.06	89.23
VOW3	9.91	29.17	35.77
Mean	25.91	41.08	54.57
Median	21.50	41.18	56.37
Min	1.92	3.37	11.02
Max	61.92	83.80	110.87

The table reports the results of Ljung-Box statistics on 5, 10 and 15 lagged standardized residuals derived from the model for deseasonalized trade durations. The critical value for LB(5), LB(10), and LB(15), are 11.07, 18.30 and 24.99, respectively.

Table A.4: Estimation Results for Quote Durations

	Autoregressive Part																	Market-related variables					
	δ_1	δ_2	δ_3	δ_4	δ_5	δ_6	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_6	Const	$1.\epsilon_{trade,t-1}$	$\epsilon_{trade,t}$	$\epsilon_{trade,t-1}$	$Exp.Trad.Dur_{t-1}$	Del.Spread	Ave.Spread	Sqrt(Vol)	Abs(sign.vol)	Back.Quo.Dur	ΔEWS
ADS	0.445***	0.138***					0.083***						0.358***	0.003**	0.265***	-0.010***	0.014***	-13.978***	-2.992***	-0.634***	0.076***	-0.0004***	0.169***
ALV	1.153***	-0.157***					0.070***	-0.063***					-0.090***	0.004***	0.390***	-0.294***	-0.065***	-30.990***	0.999***	-0.067***	0.009***	-0.001***	0.693***
BAS	0.244***	0.140***	0.059***	0.088***	0.154***		0.066***	0.024***	0.011***	0.011***	0.004***		-0.039***	0.030***	0.352***	0.085***	-0.003***	-16.084***	-3.202***	-0.485***	0.100***	0.003***	0.153***
BAYN	0.444***	0.218***					0.071***						0.503***	0.050***	0.224***	0.115***	0.049***	-19.299***	-6.083***	-0.761***	0.074***	-0.004***	0.096***
BEI	0.367***	0.102***					0.075***						0.608***	0.016***	0.507***	0.010***	0.078***	-10.240***	-7.274***	-0.783***	0.077***	0.003***	0.075***
BMW	0.298***	0.207***	0.119***	0.138***			0.061***	0.009***	0.001***	0.000			0.276***	0.028***	0.308***	0.033***	-0.138***	-16.984***	-1.422***	-0.696***	0.071***	0.003***	0.117***
CBK	0.257***	0.088***	0.034***	0.029***	0.046***	0.058***	0.075***	0.019***	0.016***	0.010***	0.013***	0.0106***	0.105***	0.012***	0.408***	0.047***	0.112***	-4.310***	-3.042***	-0.816***	0.113***	0.017***	0.094***
DAI	0.285***	0.089***	0.110***				0.064***	0.023***	0.015***				0.434***	0.024***	0.276***	0.064***	0.125***	-11.850***	-4.890***	-0.815***	0.075***	0.012***	0.034***
DB1	1.026***	-0.063***					0.021***						-0.022***	0.013***	0.275***	-0.212***	0.003***	-9.833***	-0.443***	-0.042***	0.020***	-0.001***	0.151***
DBK	0.304***	0.054***	0.106***				0.059***	0.027***	0.017***				0.097***	0.053***	0.312***	0.075***	0.188***	-9.747***	-4.362***	-0.722***	0.117***	0.011***	0.161***
DPW	0.506***	0.118***					0.078***						0.280***	0.023***	0.333***	0.018***	0.126***	-20.836***	-2.712***	-0.744***	0.075***	0.001***	0.270***
DTE	0.474***	0.084***	0.174***				0.085***	0.013***	0.010***				0.165***	0.047***	0.305***	0.137***	-0.040***	-15.974***	-1.801***	-0.728***	0.061***	-0.008***	0.216***
EOAN	0.298***	0.094***	0.063***	0.046***	0.094***		0.076***	0.029***	0.019***	0.009***	0.010***		0.006***	0.021***	0.346***	0.093***	0.072***	-23.975***	-3.750***	-0.561***	0.112***	-0.002***	0.176***
FME	0.346***	0.089***					0.071***						0.798***	-0.008***	0.256***	0.024***	0.125***	-8.936***	-4.765***	-0.891***	0.064***	0.0003***	0.015***
FRE	0.455***	0.174***					0.061***						0.620***	0.018***	0.256***	0.006***	0.025***	-9.085***	-5.140***	-0.610***	0.077***	-0.001***	0.127***
HEI	0.404***	0.217***					0.073***						0.632***	0.024***	0.257***	-0.032***	-0.098***	-11.321***	-1.703***	-0.824***	0.077***	0.003***	0.068***
HEN3	0.353***	0.348***					0.065***						0.378***	0.051***	0.262***	0.001	-0.124***	-9.884***	-1.322***	-0.709***	0.070***	0.003***	0.080***
IFX	0.404***	0.151***					0.072***						0.281***	0.038***	0.313***	-0.004***	0.036***	-6.110***	-3.058***	-0.712***	0.078***	0.011***	0.142***
LHA	0.207***	0.110***	0.135***				0.075***	0.024***	0.025***				0.155***	0.006***	0.357***	0.148***	0.146***	-7.002***	-4.456***	-0.693***	0.109***	0.003***	0.102***
LIN	0.612***	0.137***					0.055***						0.395***	0.038***	0.279***	-0.002	0.060***	-22.184***	-3.455***	-0.545***	0.074***	-0.002***	0.349***
MAN	0.397***	0.169***					0.079***						0.167***	0.016***	0.266***	-0.037***	0.034***	-2.751***	-3.030***	-0.566***	0.079***	0.006***	0.015***
MEO	0.343***	0.192***					0.058***						0.050***	0.074***	0.333***	-0.088***	-0.051***	-10.165***	-1.729***	-0.425***	0.078***	0.009***	0.179***
MRK	0.350***	0.217***					0.067***						0.602***	0.004**	0.193***	0.067***	-0.030***	-8.816***	-3.437***	-0.859***	0.078***	0.005***	0.108***
MUV2	0.444***	0.132***					0.066***						0.618***	0.031***	0.279***	0.108***	0.135***	-13.336***	-7.448***	-0.790***	0.053***	0.0004***	0.141***
RWE	0.375***	0.136***					0.067***						0.469***	0.029***	0.208***	0.023***	0.124***	-11.607***	-4.838***	-0.784***	0.079***	0.002***	0.091***
SAP	0.325***	0.121***	0.049***	0.141***			0.060***	0.020***	0.014***	0.010***			0.497***	0.051***	0.241***	0.063***	0.075***	-22.243***	-7.875***	-0.771***	0.102***	-0.0002*	0.166***
SDF	0.405***	0.104***					0.071***						0.498***	0.038***	0.370***	-0.012***	0.068***	-0.885***	-4.028***	-0.777***	0.078***	0.004***	0.043***
SIE	0.268***	0.150***	0.103***				0.066***	0.020***	0.016***				0.358***	0.022***	0.251***	0.110***	0.129***	-12.091***	-4.953***	-0.818***	0.049***	-0.006***	0.125***
TKA	0.326***	0.021***	-0.011***	0.091***			0.069***	0.017***	0.011***	0.022***			0.260***	0.036***	0.307***	0.058***	0.187***	-5.648***	-3.181***	-0.764***	0.162***	0.006***	0.108***
VOW3	0.233***	0.137***	0.126***				0.083***	0.041***	0.012***				0.318***	0.016***	0.317***	0.117***	0.138***	-7.336***	-3.789***	-0.878***	0.080***	0.003***	0.044***
Mean	$\sum\delta_j$: 0.600						$\sum\rho_j$: 0.084						0.326	0.027	0.301	0.024	0.050	-12.450	-3.639	-0.676	0.079	0.003	0.144
Median	$\sum\delta_j$: 0.572						$\sum\rho_j$: 0.074						0.338	0.024	0.292	0.029	0.064	-10.780	-3.446	-0.736	0.077	0.003	0.121
Min	$\sum\delta_j$: 0.427						$\sum\rho_j$: 0.007						-0.090	-0.008	0.193	-0.294	-0.138	-30.990	-7.875	-0.891	0.009	-0.008	0.015
Max	$\sum\delta_j$: 0.996						$\sum\rho_j$: 0.144						0.798	0.074	0.507	0.148	0.188	-0.885	0.999	-0.042	0.162	0.017	0.693

The table reports the estimated results for deseasonalized trade duration and the distribution of the estimated parameters. δ and ρ are parameters for the logACD model: $\phi_k = \exp\left(\mu + \sum_{j=1}^{p} \rho_j \epsilon_{k-j} + \rho_{j+1}\epsilon_{k-1} d_{k-1} + \sum_{j=1}^{l} \delta_j \ln \phi_{k-j} + \Phi' V_{k-1}\right)$, and market-related variables include variables capturing volume and liquidity of the market. ***, ** and * denote either coefficient estimates that are significantly different from zero or test statistics that are significant at the 1%, 5% and 10%, respectively.

Table A.5: Ljung-box test for Quote Duration

Ticker	LB(5)	LB(10)	LB(15)
ADS	24.77	46.60	62.50
ALV	49.49	69.49	72.78
BAS	3.81	9.53	26.73
BAYN	6.02	42.13	90.68
BEI	7.19	16.88	23.01
BMW	2.54	4.51	19.22
CBK	26.78	69.83	90.18
DAI	7.63	44.47	80.00
DB1	39.99	50.97	57.26
DBK	10.68	61.96	83.50
DPW	1.88	19.50	57.70
DTE	0.75	7.98	77.78
EOAN	1.51	22.65	88.39
FME	13.85	54.10	74.04
FRE	4.93	16.90	24.73
HEI	3.36	28.36	43.69
HEN3	3.93	9.42	24.82
IFX	12.92	50.75	84.54
LHA	3.54	36.88	73.94
LIN	1.65	7.33	15.89
MAN	13.87	63.08	79.31
MEO	22.06	42.32	66.42
MRK	9.21	23.43	34.71
MUV2	7.21	24.80	48.19
RWE	13.28	46.51	84.82
SAP	0.80	9.88	59.88
SDF	16.41	34.65	42.82
SIE	1.24	27.91	80.59
TKA	6.65	53.16	87.39
VOW3	0.83	35.00	60.68
Mean	10.63	34.37	60.54
Median	6.92	34.83	64.46
Min	0.75	4.51	15.89
Max	49.49	69.83	90.68

The table reports the results of Ljung-Box statistics on 5, 10 and 15 lagged standardized residuals derived from the model for deseasonalized quote durations. The critical value for LB(5), LB(10), and LB(15), are 11.07, 18.30 and 24.99, respectively.

Table A.6: Ljung-Box Statistics for Activity, Direction and Size Factors of EWS^{Low}

	Activity			Direction			Size		
Ticker	LB(5)	LB(10)	LB(15)	LB(5)	LB(10)	LB(15)	LB(5)	LB(10)	LB(15)
ADS	2263.90	3013.53	3380.36	4262.02	4272.98	4278.42	11406.10	16103.75	19011.01
ALV	10714.69	12349.57	13368.93	15722.80	15732.33	15742.48	19886.67	25562.39	30139.48
BAS	4107.00	4820.26	5180.01	15840.70	15869.68	15872.90	14124.74	18961.75	22182.30
BAYN	1937.76	2298.52	2545.57	11216.49	11230.11	11236.36	10188.80	14241.93	17160.31
BEI	1004.39	1248.55	1348.54	2382.94	2391.76	2394.56	5514.75	7027.23	8268.67
BMW	3556.41	3997.27	4366.46	12238.12	12257.00	12266.01	14236.93	18480.90	22128.39
CBK	18053.69	21435.57	23510.97	14967.53	14997.56	15006.87	41313.46	56079.61	65918.34
DAI	4654.86	5547.40	6146.60	15327.52	15339.90	15347.93	20517.65	27768.33	33340.29
DB1	3175.01	4250.51	4957.41	5426.88	5433.84	5443.18	17635.42	25766.27	32212.07
DBK	7359.92	8688.86	9470.23	18330.57	18350.85	18359.75	28513.96	38358.94	46838.19
DPW	5474.27	6252.29	6628.99	5624.87	5633.68	5637.13	6345.21	8151.47	9277.84
DTE	15592.69	18147.14	19849.47	7797.13	7811.21	7814.32	13836.69	17561.72	20360.46
EOAN	13689.18	17370.81	19942.26	19361.56	19368.70	19371.93	32387.69	45657.26	56558.42
FME	1537.04	2007.41	2313.07	3941.67	3948.92	3951.70	14163.88	20383.63	24706.10
FRE	1719.88	2165.79	2437.47	2864.18	2880.57	2888.77	14111.19	19542.96	23078.45
HEI	3662.05	4718.42	5407.12	5141.84	5160.78	5177.97	16046.19	23996.45	28985.25
HEN3	2219.38	2754.75	3129.65	4612.79	4635.70	4643.60	13847.51	19808.52	23941.81
IFX	3665.74	4225.39	4534.23	6867.77	6893.79	6896.89	13943.32	18573.85	21870.79
LHA	3964.37	4507.99	4757.31	4458.94	4469.85	4471.96	8879.08	12653.70	15214.17
LIN	4232.02	5031.44	5431.57	4265.66	4268.82	4270.40	6235.13	8158.98	9050.37
MAN	5437.06	7010.95	8154.88	6815.45	6846.41	6859.83	26909.94	42463.55	55094.45
MEO	2650.68	3164.90	3512.38	5463.39	5481.36	5483.98	10071.74	13427.03	15521.66
MRK	1637.03	2061.70	2316.10	3938.26	3950.28	3953.84	12645.13	17275.60	21543.58
MUV2	5378.08	6008.49	6282.16	6488.92	6493.50	6498.73	5371.05	6641.75	7359.34
RWE	3673.00	4368.87	4734.41	10403.57	10421.80	10437.37	14362.98	20931.58	26526.60
SAP	3860.85	4507.64	4965.08	13525.71	13541.85	13547.17	12349.95	15928.96	18783.85
SDF	2062.00	2469.94	2672.47	5502.76	5509.43	5512.05	13626.33	20052.79	24394.20
SIE	3922.55	4484.47	4719.65	16888.09	16901.99	16905.70	16688.61	22366.07	26210.41
TKA	3082.99	3593.17	3997.47	7202.92	7229.28	7239.13	17774.21	24979.58	30200.80
VOW3	7517.48	8456.62	9012.72	5971.91	5980.58	5981.28	10548.54	13924.77	16366.27

The table reports the Ljung-Box statistic on deseasonalized trade durations, deseasonalized quote durations, activity, direction and size factors of the EWS^{High} for different stocks at 5, 10 and 15 lags . The critical value for LB(5), LB(10), and LB(15) are 11.07, 18.30 and 24.99, respectively.

Table A.7: Estimation Results for Liquidity Activity Factor of EWS^{Low}

	GLARMA						Market-related variables								
	γ_1^A	γ_2^A	γ_3^A	λ_1^A	λ_2^A	λ_3^A	Const	Exp.Tr.Dur.	Exp.Quo.Dur.	Del.Spread	Ave.Spread	Sqrt(Vol)	Abs(sign.vol)	Back.Quo.Dur	ΔEWS
ADS	0.940***			0.408***	-0.311***		-1.570***	0.064***	-0.090***	-1.322***	8.601***	0.2509***	-0.105***	0.008***	0.009
ALV	1.255***	-0.200	-0.069	1.016***	-0.978***	-0.001	-2.167***	0.300***	-0.291***	8.664***	7.214***	0.1167***	-0.049***	0.019***	0.200***
BAS	0.786***			0.408***	-0.199***		-1.272***	0.078***	-0.036***	0.160	10.377***	0.1345***	-0.034***	0.012***	0.025***
BAYN	0.864***			0.374***	-0.251***		-1.372***	0.020	-0.049***	-2.027***	12.132***	0.2176***	-0.115***	0.007***	0.017
BEI	0.766***			0.380***	-0.159***		-1.223***	0.079***	-0.052***	0.286	6.446***	0.2398***	-0.055***	0.002***	-0.008
BMW	0.761***			0.414***	-0.186***		-1.246***	0.072***	-0.057***	0.172	8.366***	0.1799***	-0.027***	0.012***	0.017**
CBK	0.623***			0.500***	-0.073***		-1.613***	0.077***	-0.063***	0.989***	10.500***	0.2685***	-0.046***	0.010***	0.078***
DAI	0.882***			0.389***	-0.248***		-1.453***	-0.021*	-0.043***	-4.036***	8.994***	0.2664***	-0.059***	0.013***	-0.001
DB1	0.952***			0.468***	-0.374***		-1.590***	0.077***	-0.020	-1.550***	8.721***	0.1025***	-0.049***	0.005***	0.030***
DBK	0.824***			0.530***	-0.284***		-1.607***	0.018**	-0.053***	-0.337	6.046***	0.2373***	-0.054***	0.013***	-0.004
DPW	0.600***			0.722***	-0.272***		-1.644***	0.191***	-0.125***	1.567***	12.588***	0.2445***	-0.044***	0.008***	0.022**
DTE	1.527***	-0.797***	0.047	1.174***	-1.605***	0.741***	-3.652***	0.489***	-0.362***	11.445***	29.578***	0.2337***	0.009	0.015***	0.169***
EOAN	-0.778***	-0.444***	0.387***	0.694***	0.813***	0.624***	-2.836***	0.172***	-0.174***	13.456***	36.830***	0.1470***	-0.023**	0.020***	0.334***
FME	0.897***			0.303***	-0.182***		-1.257***	0.046***	-0.097***	-1.194***	6.824***	0.2678***	-0.038***	0.006***	-0.002
FRE	0.710***			0.451***	-0.159***		-1.257***	0.096***	-0.083***	1.556***	6.872***	0.1319***	-0.063***	0.003***	-0.003
HEI	0.966***			0.455***	-0.395***		-1.556***	0.077***	-0.077***	0.540	7.340***	0.1569***	-0.026**	0.005***	-0.001
HEN3	0.932***			0.417***	-0.324***		-1.426***	0.073***	-0.122***	1.692***	7.794***	0.1659***	-0.004	0.006***	-0.032***
IFX	0.586***			0.462***	-0.086***		-1.151***	0.092***	-0.089***	1.442***	6.705***	0.1881***	-0.051***	0.011***	0.013*
LHA	0.565***			0.649***	-0.209***		-1.373***	0.259***	-0.128***	2.147***	10.601***	0.1775***	-0.012	0.009***	0.036***
LIN	0.530***			0.766***	-0.262***		-1.802***	0.342***	-0.202***	7.737***	13.712***	0.0801***	-0.017*	0.007***	0.089***
MAN	0.714***	0.662***	-0.384***	0.495***	-0.157**	-0.316***	-2.061***	0.048***	-0.083***	1.753***	8.010***	0.1346***	-0.041***	0.008***	0.001
MEO	0.751***			0.436***	-0.165***		-1.298***	0.135***	-0.084***	2.649***	8.238***	0.1294***	-0.035***	0.006***	-0.054***
MRK	0.697***			0.376***	-0.124***		-1.162***	0.168***	-0.126***	1.283***	8.157***	0.1518***	0.005	0.005***	0.017
MUV2	0.265***			0.745***	0.078		-2.376***	0.470***	-0.295***	8.125***	19.592***	0.1483***	0.006	0.008***	0.188***
RWE	0.831***			0.505***	-0.313***		-1.515***	0.047***	-0.044***	-0.144	9.885***	0.2165***	-0.042***	0.006***	-0.046***
SAP	0.914***			0.489***	-0.369***		-1.703***	0.029**	-0.082***	0.899*	11.211***	0.1779***	-0.053***	0.007***	-0.020*
SDF	0.597***			0.357***	-0.030		-1.127***	0.072***	-0.026***	-1.717***	9.370***	0.2283***	-0.014	0.007***	0.052***
SIE	0.819***			0.466***	-0.284***		-1.516***	0.056***	-0.034***	1.913***	10.469***	0.2065***	-0.035***	0.004***	-0.016*
TKA	0.842***			0.435***	-0.240***		-1.189***	0.073***	-0.026***	-0.200	6.049***	0.1999***	-0.029***	0.005***	0.003
VOW3	0.812***			0.783***	-0.458***		-1.492***	0.109***	-0.108***	-1.160***	4.131***	0.235***	-0.049***	0.011***	0.074***
Mean	$\sum \gamma_j^A$: 0.721			$\sum \lambda_j^A$: 0.310			-1.617	0.127	-0.104	1.826	10.712	0.188	-0.038	0.009	0.039
Median	$\sum \gamma_j^A$: 0.799			$\sum \lambda_j^A$: 0.224			-1.503	0.077	-0.083	0.944	8.661	0.184	-0.040	0.007	0.015
Min	$\sum \gamma_j^A$: -0.835			$\sum \lambda_j^A$: 0.021			-3.652	-0.021	-0.362	-4.036	4.131	0.080	-0.115	0.002	-0.054
Max	$\sum \gamma_j^A$: 0.992			$\sum \lambda_j^A$: 2.131			-1.127	0.489	-0.020	13.456	36.830	0.268	0.009	0.020	0.334

The table reports the estimated results for the model of the activity factor of Z^{Low} and the distribution of the estimated parameters. γ^A and λ^A are parameters for GLARMA structure: $g_k^A = \sum_{j=1}^{p} \gamma_j^A g_{k-j}^A + \sum_{j=1}^{l} \lambda_j^A A_{k-j}$, and market-related variables include variables capturing duration, volume and liquidity of the market. For the sake of brevity, we do not present the estimation results of seasonality dummy variables. ***, ** and * denote either coefficient estimates that are significantly different from zero or test statistics that are significant at the 1%, 5% and 10%, respectively.

Table A.8: In-sample tests for EWS Activity Factor of EWS^{low}

Ticker	LB(5)	LB(10)	LB(15)	R-sqrt	ROC	#_Acc
ADS	44.021	48.040	59.783	19.83%	0.618	59.16%
ALV	26.403	64.356	92.971	40.37%	0.719	69.70%
BAS	9.526	11.952	13.915	27.90%	0.589	60.57%
BAYN	3.320	6.384	7.879	24.47%	0.586	58.80%
BEI	2.891	3.842	5.091	14.29%	0.591	57.93%
BMW	10.397	11.119	22.330	22.20%	0.595	58.05%
CBK	9.730	24.582	62.335	22.93%	0.642	60.76%
DAI	11.103	16.697	22.586	23.40%	0.600	59.01%
DB1	50.529	51.917	57.842	21.70%	0.631	59.91%
DBK	23.452	29.111	39.509	32.33%	0.612	63.64%
DPW	10.376	19.499	28.645	19.55%	0.657	62.25%
DTE	52.705	72.464	94.669	46.07%	0.769	72.49%
EOAN	42.447	58.580	87.181	44.65%	0.717	70.70%
FME	8.017	12.805	19.908	13.97%	0.610	59.30%
FRE	3.084	4.663	11.829	17.67%	0.621	59.27%
HEI	56.213	57.060	58.825	19.25%	0.619	59.07%
HEN3	27.584	31.653	39.311	20.60%	0.608	58.58%
IFX	8.232	19.780	34.010	20.60%	0.604	58.17%
LHA	9.985	17.112	22.136	18.75%	0.654	61.46%
LIN	11.806	23.285	25.782	23.56%	0.690	64.31%
MAN	11.778	19.493	25.860	27.86%	0.632	62.17%
MEO	3.970	11.300	18.178	24.10%	0.611	59.52%
MRK	2.757	7.157	14.726	18.15%	0.608	58.22%
MUV2	12.585	18.240	21.078	26.06%	0.711	65.69%
RWE	11.788	22.205	23.118	30.03%	0.604	62.12%
SAP	18.729	23.372	26.166	34.62%	0.600	65.55%
SDF	3.643	8.764	21.495	16.08%	0.608	58.30%
SIE	6.009	9.700	26.749	31.96%	0.588	63.65%
TKA	29.774	36.151	38.478	20.90%	0.598	57.84%
VOW3	20.357	21.744	26.612	20.31%	0.658	62.10%
Mean	18.107	25.434	34.967	24.81%	0.632	61.61%
Median	11.440	19.640	26.013	22.57%	0.611	60.24%
Min	2.757	3.842	5.091	13.97%	0.586	57.84%
Max	56.213	72.464	94.669	46.07%	0.769	72.49%

The table reports the results of in-sample tests for the activity factor model. LB(5), LB(10) and LB(15) are Ljung-Box statistics on 5, 10 and 15 lagged standardized residuals. The critical value for LB(5), LB(10), and LB(15), are 11.07, 18.30 and 24.99, respectively. R-sqrt is the McFadden's R squared, defined as $R^2_{McFaden} = 1 - \frac{log(L_c)}{log(L_{null})}$ where L_c denotes the likelihood value from the current fitted model and L_{null} denotes the corresponding value for the null model. ROC relates the Receiver Operating Characteristic test. #_Acc is the Count accuracy that takes 50% as the threshold to have value one.

Table A.9: Estimation Results for Direction Factor of EWS^{Low}

	GLARMA						Market-related variables							
	γ_1^D	γ_2^D	γ_3^D	λ_1^D	λ_2^D	λ_3^D	Const	Exp.QQ.Dur.	Del.Spread	Ave.Spread	Sqrt(Vol)	Abs(sign.vol)	Back.Quo.Dur	ΔEWS
ADS	0.636***			-0.736***	-0.136***		0.596***	-0.035***	26.883***	-17.997***	0.231***	-0.1079***	-0.011***	-0.509***
ALV	0.584***			-1.249***	-0.409***		0.528***	0.006	21.411***	-13.675***	0.045*	0.0046	-0.008***	-1.050***
BAS	1.294***	-0.436***		-1.536***	0.979***		0.777***	-0.022***	36.437***	-24.726***	0.045**	-0.1068***	-0.032***	-0.485***
BAYN	-0.316***	0.568***		-1.748***	-1.557***		0.705***	-0.021***	35.112***	-23.980***	0.107***	-0.1922***	-0.027***	-0.279***
BEI	0.569***			-0.569***	-0.230***		0.795***	-0.037***	21.669***	-14.876***	0.067*	-0.0363*	-0.007***	-0.462***
BMW	0.635***			-1.081***	-0.139***		0.528***	-0.011***	27.948***	-16.472***	0.060***	-0.0578***	-0.019***	-0.567***
CBK	0.601***			-0.923***	-0.069***		0.554***	-0.021***	19.887***	-11.651***	0.122***	-0.0092	-0.016***	-0.430***
DAI	0.443***	0.090		-1.440***	-0.349		0.887***	-0.045***	35.630***	-25.644***	0.159***	-0.0655***	-0.039***	-0.470***
DB1	0.609***			-0.936***	-0.097***		0.391***	-0.022***	24.707***	-8.659***	0.037*	-0.0581***	-0.008***	-0.437***
DBK	-0.314***	0.568***		-1.706***	-1.529***		0.831***	-0.015***	30.080***	-28.081***	0.109***	-0.0422**	-0.038***	-0.352***
DPW	0.735***	-0.156**		-0.679***	-0.222***		0.462***	-0.014**	26.420***	-12.658***	0.181***	-0.0550**	-0.012***	-0.722***
DTE	0.437***			-1.031***	-0.484***		0.577***	-0.006	24.839***	-14.158***	0.125***	-0.0384	-0.005***	-1.109***
EOAN	-0.243***	0.551***		-2.207***	-1.667***		0.804***	-0.017**	24.234***	-15.839***	0.089***	0.0268	-0.005*	-0.368***
FME	0.654***			-0.671***	-0.076***		0.396***	-0.041***	23.643***	-11.653***	0.234***	-0.0375**	-0.012***	-0.406***
FRE	0.593***			-0.491***	-0.167***		0.672***	-0.041***	20.385***	-11.680***	0.076**	-0.0732***	-0.008***	-0.431***
HEI	0.646***			-0.663***	-0.139***		0.450***	-0.031***	19.944***	-11.832***	0.161***	-0.0507***	-0.009***	-0.421***
HEN3	0.633***			-0.796***	-0.108***		0.543***	-0.032***	20.778***	-15.465***	0.172***	-0.0540***	-0.009***	-0.432***
IFX	0.592***			-0.661***	-0.239***		0.576***	-0.026***	23.902***	-15.267***	0.100***	-0.0644***	-0.013***	-0.565***
LHA	0.580***			-0.725***	-0.143***		0.381***	-0.009*	22.276***	-11.409***	0.155***	-0.0319**	-0.010***	-0.479***
LIN	0.609***			-0.911***	-0.103**		0.520***	-0.007	18.934***	-10.539***	0.109***	-0.0500**	-0.005***	-0.586***
MAN	0.652***			-0.964***	0.011		0.381***	-0.031***	21.418***	-10.086***	0.098***	-0.0292**	-0.010***	-0.388***
MEO	0.629***			-0.965***	-0.059*		0.621***	-0.039***	26.343***	-18.549***	0.066**	-0.0423**	-0.009***	-0.500***
MRK	0.691***			-0.773***	-0.042		0.436***	-0.029***	23.148***	-14.276***	0.152***	-0.0283	-0.007***	-0.480***
MUV2	0.500***			-0.834***	-0.643***		0.605***	0.034***	18.813***	-13.586***	0.143***	-0.0564**	-0.004***	-1.196***
RWE	-0.329***	0.621***		-1.629***	-1.554***		0.588***	-0.029***	26.432***	-18.233***	0.096***	-0.0509**	-0.016***	-0.445***
SAP	-0.788***	0.466***	0.294**	-1.973***	-2.669***	-0.779**	0.847***	-0.028***	34.701***	-27.581***	0.042	-0.0650***	-0.022***	-0.320***
SDF	0.986***	-0.242		-0.790***	0.199		0.572***	-0.014***	24.036***	-15.646***	0.227***	-0.0595***	-0.024***	-0.345***
SIE	-0.331***	0.572***		-2.054***	-1.882***		1.090***	-0.009**	33.232***	-35.471***	0.010	-0.0191	-0.032***	-0.285***
TKA	-0.132	0.457***		-1.065***	-0.766***		0.610***	-0.020***	28.023***	-17.041***	0.101***	-0.0155	-0.019***	-0.295***
VOW3	1.141***	-0.362***		-0.901***	0.390***		0.687***	-0.003	21.590***	-15.343***	0.181***	-0.061***	-0.018***	-0.422***
Mean	$\sum \gamma_j^D$: 0.533			$\sum \lambda_j^D$: -1.579			0.614	-0.021	25.429	-16.736	0.117	-0.051	-0.015	-0.508
Median	$\sum \gamma_j^D$: 0.593			$\sum \lambda_j^D$: -1.003			0.583	-0.022	24.135	-15.305	0.108	-0.051	-0.011	-0.441
Min	$\sum \gamma_j^D$: -0.028			$\sum \lambda_j^D$: -5.421			0.381	-0.045	18.813	-35.471	0.010	-0.192	-0.039	-1.196
Max	$\sum \gamma_j^D$: 0.858			$\sum \lambda_j^D$: -0.511			1.090	0.034	36.437	-8.659	0.234	0.027	-0.004	-0.279

The table reports the estimated results for the model of the direction factor of Z^{Low} and the distribution of the estimated parameters. γ^D and λ^D are parameters for GLARMA structure: $g_k^D = \sum_{j=1}^{p} \gamma_j^D g_{k-j}^D + \sum_{j=1}^{l} \lambda_j^D D_{k-j}$, and market-related variables include variables capturing duration, volume and liquidity of the market. For the sake of brevity, we do not present the estimation results of seasonality dummy variables. ***, ** and * denote either coefficient estimates that are significantly different from zero or test statistics that are significant at the 1%, 5% and 10%, respectively.

Table A.10: In-sample tests for EWS Direction Factor of EWS^{low}

Ticker	LB(5)	LB(10)	LB(15)	R-sqrt	ROC	#_Acc
ADS	42.628	49.748	58.858	36.54%	0.807	74.48%
ALV	58.857	71.547	77.410	50.79%	0.875	82.83%
BAS	8.501	49.369	64.249	42.50%	0.852	78.27%
BAYN	9.944	23.216	29.500	44.45%	0.864	79.53%
BEI	5.442	10.754	12.848	33.26%	0.792	73.08%
BMW	9.872	29.203	59.222	38.86%	0.825	76.25%
CBK	42.181	69.001	72.996	35.43%	0.808	74.66%
DAI	9.529	16.674	25.804	43.16%	0.852	78.19%
DB1	33.289	55.562	57.286	35.32%	0.810	75.05%
DBK	25.728	33.059	39.995	43.76%	0.860	79.17%
DPW	22.580	33.983	38.533	42.64%	0.845	78.41%
DTE	8.191	13.944	16.673	52.84%	0.874	83.92%
EOAN	15.452	38.557	44.336	60.25%	0.917	87.75%
FME	21.008	28.535	34.325	34.04%	0.795	73.08%
FRE	17.067	25.496	28.599	31.10%	0.773	71.05%
HEI	5.734	39.836	47.088	32.21%	0.786	72.50%
HEN3	20.853	38.412	45.239	33.34%	0.794	73.41%
IFX	24.274	50.654	71.168	35.43%	0.803	73.85%
LHA	7.506	9.976	17.584	36.59%	0.810	74.65%
LIN	8.118	14.480	23.097	39.95%	0.832	77.84%
MAN	0.244	2.215	7.754	34.27%	0.799	74.25%
MEO	15.223	47.557	54.420	36.83%	0.814	75.66%
MRK	26.733	60.896	71.922	34.10%	0.800	73.53%
MUV2	49.866	53.084	53.447	50.81%	0.875	82.86%
RWE	43.513	55.877	68.253	44.01%	0.856	79.58%
SAP	69.833	84.509	97.393	47.87%	0.879	81.35%
SDF	1.827	5.635	7.272	33.54%	0.801	73.02%
SIE	23.971	28.765	36.255	46.15%	0.871	80.06%
TKA	2.409	4.320	23.224	34.84%	0.808	73.85%
VOW3	33.542	41.788	47.014	38.37%	0.825	76.04%
Mean	22.131	36.222	44.392	40.11%	0.830	76.94%
Median	18.960	36.197	44.787	37.60%	0.819	75.85%
Min	0.244	2.215	7.272	31.10%	0.773	71.05%
Max	69.833	84.509	97.393	60.25%	0.917	87.75%

The table reports the results of in-sample tests for direction model. LB(5), LB(10) and LB(15) are Ljung-Box statistics on 5, 10 and 15 lagged standardized residuals. The critical value for LB(5), LB(10), and LB(15), are 11.07, 18.30 and 24.99, respectively. R-sqrt is the McFadden's R squared, defined as $R^2_{McFaden} = 1 - \frac{log(L_c)}{log(L_{null})}$ where L_c denotes the likelihood value from the current fitted model and L_{null} denotes the corresponding value for the null model. ROC relates the Receiver Operating Characteristic test. #_Acc is the Count accuracy that takes 50% as the threshold to have value one.

Table A.11: Estimation Results for Liquidity Size Factor of EWS^{Low}

	GLARMA						Market-related variables							
	γ_1^{Siz}	γ_2^{Siz}	γ_3^{Siz}	λ_1^{Siz}	λ_2^{Siz}	λ_3^{Siz}	Const	Exp.QQ.Dur.	Del.Spread	Ave.Spread	Sqrt(Vol)	Abs(sign.vol)	Back.Quo.Dur	ΔEWS
ADS	0.995***			-0.294***	0.289***		2.499***	0.002***	1.831***	-7.954***	-0.161***	-0.002	0.002**	0.067***
ALV	1.141***	0.268***	-0.410***	-0.486***	0.605***	-0.122***	2.699***	0.000	-1.570***	-12.510***	-0.127***	-0.060*	0.012***	-0.120***
BAS	1.243***	-0.011	-0.250***	-0.462***	0.554***	-0.117***	3.067***	0.003**	-1.170*	-13.727***	-0.221***	0.027	0.027***	0.095***
BAYN	0.685***	0.150***		-0.414***	0.253***		3.582***	0.001	0.304	-14.558***	-0.246***	-0.176***	0.017***	0.065***
BEI	0.954***			-0.247***	0.218***		1.755***	0.002***	1.237***	-3.392***	-0.172***	0.033**	0.001*	0.063***
BMW	0.964***	-0.039		-0.404***	0.324***		2.823***	0.003***	2.121***	-8.337***	-0.243***	-0.004	0.016***	0.127***
CBK	0.912***	-0.011		-0.228***	0.167***		2.274***	0.004***	0.059	-9.723***	-0.174***	-0.090***	0.029***	0.021***
DAI	0.102	0.899***	-0.115***	-0.434***	-0.034	0.349***	3.020***	0.002***	1.839***	-11.797***	-0.231***	-0.011	0.025***	0.105***
DB1	0.453***	0.306***		-0.202***	0.056***		2.393***	0.002***	1.012*	-9.917***	-0.158***	0.033	0.008***	0.045***
DBK	1.560***	-0.473***	-0.099***	-0.453***	0.686***	-0.244***	3.244***	0.006***	2.175***	-13.587***	-0.293***	-0.091***	0.033***	0.114***
DPW	-0.648***			-0.372***	-0.104***		1.456***	0.001	1.241***	-4.859***	-0.130***	0.027	0.003***	0.009
DTE	-0.712***			-0.530***	-0.193***		1.677***	0.001	-1.078***	-6.875***	-0.047*	-0.006	0.003*	-0.122***
EOAN	1.445***	-0.421***	-0.053	-0.430***	0.569***	-0.177***	3.946***	0.010***	-0.860	-26.599***	-0.206***	-0.126***	0.054***	-0.067***
FME	0.590***			-0.183***	0.069***		2.180***	0.002***	1.279***	-8.037***	-0.161***	-0.031***	0.000	0.033***
FRE	0.995***			-0.209***	0.204***		1.891***	0.001***	0.373***	-5.661***	-0.202***	0.012	0.001**	0.050***
HEI	0.636***	0.172***		-0.221***	0.103***		1.987***	0.002***	0.824**	-6.561***	-0.171***	-0.037**	0.004***	0.085***
HEN3	0.912***			-0.270***	0.209***		2.205***	0.002***	0.896***	-4.702***	-0.186***	-0.039***	0.003***	0.069***
IFX	0.957***			-0.289***	0.259***		2.168***	0.002***	0.532***	-4.827***	-0.203***	-0.026***	0.005***	0.096***
LHA	0.897***			-0.215***	0.171***		1.542***	0.001*	0.523***	-3.764***	-0.125***	-0.013	0.001*	0.034***
LIN	0.887***			-0.304***	0.256***		1.596***	0.001	-0.050	-5.163***	-0.122***	0.044*	0.002**	-0.051***
MAN	1.400***	-0.194	-0.211***	-0.187***	0.229***	-0.047***	2.658***	0.004***	1.531***	-9.273***	-0.252***	-0.049***	0.014***	0.040***
MEO	-0.333	0.641***	0.179	-0.338***	-0.143	0.111	2.811***	0.001***	0.518	-11.271***	-0.279***	-0.076**	0.004***	0.087***
MRK	0.543***			-0.275***	0.109***		2.398***	0.002***	1.127***	-5.551***	-0.262***	-0.013	0.003***	0.067***
MUV2	-0.653***			-0.472***	-0.126***		1.726***	0.000	-0.799**	-7.046***	-0.094***	0.016	0.001	-0.102***
RWE	0.708***	0.098		-0.345***	0.172***		3.308***	0.002**	-0.741	-11.719***	-0.245***	-0.081***	0.016***	0.108***
SAP	0.942***	-0.026		-0.513***	0.386***		4.144***	0.003***	0.385	-17.136***	-0.179***	-0.036	0.021***	0.091***
SDF	0.993***			-0.247***	0.243***		2.023***	0.001***	1.297***	-4.840***	-0.233***	-0.026***	0.002***	0.100***
SIE	1.308***	-0.192	-0.139***	-0.391***	0.414***	-0.052	3.687***	0.003**	0.995	-14.720***	-0.268***	-0.051***	0.052***	0.082***
TKA	0.594**	0.450**	-0.119***	-0.255***	0.127*	0.076	2.393***	0.002***	0.624	-8.605***	-0.230***	-0.054***	0.008***	0.050***
VOW3	0.910***			-0.215***	0.181***		1.413***	0.001	1.025***	-3.318***	-0.116***	0.012	0.002**	-0.001
Mean	$\sum \gamma_j^{Siz}$: 0.726			$\sum \lambda_j^{Siz}$: -0.128			2.486	0.002	0.583	-9.201	-0.191	-0.030	0.012	0.041
Median	$\sum \gamma_j^{Siz}$: 0.717			$\sum \lambda_j^{Siz}$: -0.133			2.393	0.002	0.724	-8.187	-0.194	-0.026	0.005	0.064
Min	$\sum \gamma_j^{Siz}$: 0.707			$\sum \lambda_j^{Siz}$: -0.137			1.413	0.000	-1.570	-26.599	-0.293	-0.176	0.000	-0.122
Max	$\sum \gamma_j^{Siz}$: 0.696			$\sum \lambda_j^{Siz}$: -0.141			4.144	0.010	2.175	-3.318	-0.047	0.044	0.054	0.127

The table reports the estimated results for the model of the size factor of Z^{Low} and the distribution of the estimated parameters. γ^{Siz} and λ^{Siz} are parameters for GLARMA structure: $g_k^{Siz} = \sum_{j=1}^{p} \gamma_j^{Siz} g_{k-j}^{Siz} + \sum_{j=1}^{l} \lambda_j^{Siz} s_{k-j}$, and market-related variables include variables capturing duration, volume and liquidity of the market. For the sake of brevity, we do not present the estimation results of seasonality dummy variables. ***, ** and * denote either coefficient estimates that are significantly different from zero or test statistics that are significant at the 1%, 5% and 10%, respectively.

Table A.12: Ljung-Box Statistics for EWS Size Factor of EWS^{low}

Ticker	LB(5)	LB(10)	LB(15)	R-sqrt
ADS	175.50	221.53	241.47	22.53%
ALV	274.78	313.31	365.32	35.20%
BAS	255.43	299.16	335.00	36.19%
BAYN	234.61	246.84	277.05	15.46%
BEI	93.74	104.50	126.03	48.62%
BMW	223.63	269.45	284.82	43.46%
CBK	168.83	181.96	205.73	50.32%
DAI	280.53	292.45	310.84	47.18%
DB1	222.08	243.01	268.12	50.02%
DBK	358.91	411.44	474.05	61.85%
DPW	47.11	74.02	88.84	14.59%
DTE	63.85	94.66	110.36	27.80%
EOAN	443.41	470.93	496.03	26.90%
FME	206.02	247.10	273.44	38.98%
FRE	63.21	105.58	117.23	55.08%
HEI	184.26	204.58	269.54	51.62%
HEN3	234.06	265.84	301.73	4.27%
IFX	185.20	219.44	244.39	8.49%
LHA	116.35	125.76	133.11	43.47%
LIN	105.67	109.16	116.94	16.04%
MAN	522.77	654.96	766.09	60.06%
MEO	122.52	136.15	150.95	51.15%
MRK	172.85	223.75	255.55	38.80%
MUV2	73.88	93.93	125.45	39.14%
RWE	275.40	307.52	315.93	42.43%
SAP	211.65	240.69	279.33	19.71%
SDF	192.43	233.25	251.95	34.59%
SIE	408.45	466.75	506.98	48.78%
TKA	319.61	353.24	417.10	54.58%
VOW3	184.67	200.91	232.00	58.55%
Mean	214.05	247.06	278.05	38.20%
Median	199.23	236.97	268.83	40.78%
Min	47.11	74.02	88.84	4.27%
Max	522.77	654.96	766.09	61.85%

The table reports the results of Ljung-Box statistics on 5, 10 and 15 lagged standardized residuals and adjusted R^2. The critical value for LB(5), LB(10), and LB(15), are 11.07, 18.30 and 24.99, respectively.