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Investigation of the Trade Durations with Autoregressive Conditional Duration Model: Evidence from Borsa İstanbul

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ABSTRACT

This research paper explores duration dynamics within the Borsa İstanbul (BIST) stock exchange by utilizing the Autoregressive Conditional Duration (ACD) model applied to the time between consecutive trades. The investigation of an appropriate error term specification demonstrates that the Weibull ACD (WACD) model is the most suitable choice of distribution. The application of the WACD model on the ten most actively traded stocks in the market reveals cross-sectional variations in the trade duration dynamics, where the degree of duration clustering varies even among the most liquid stocks in the market. The study indicates that the duration dynamics within the Borsa İstanbul are closer to those observed in developing markets, in terms of market microstructure and intraday liquidity, rather than those in developed markets. These findings provide insights for market participants and academics to better understand the trade duration dynamics within the BIST market.

Keywords: Autoregressive Conditional Duration Model; Market Microstructure; Intraday Liquidity; Duration Clustering; High Frequency Mata.

JEL Classification Codes: C10, C22, C41, G10, G15

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INTRODUCTION

With the advances in accessibility of the low-cost intraday transaction data in recent years, finance academics and practitioners alike have embraced the studies of high frequency data. Most empirical studies, which use day-to-day data acquired by keeping either first or final observation of a time series, are evidently neglecting intraday events that may include valuable information. As the markets are compelled to be faster, traditional models are getting replaced by new ones that are using intraday data taking every single transaction into consideration. By using high frequency data and modeling it with the state-of-the-art econometric tools, a deeper knowledge of market activity and microstructure emerges. These new approaches make it possible to keep pace with the constantly increasing speed of trading in global financial markets.

Seminal studies in the market microstructure show that apart from the traditional trade variables like price, volume, number of trades etc., "time" is carrying value information and should, therefore, be closely studied as well (Easley & O'Hara, 1992; Easley et al.,1997). Inspired by these arguments, Engle and Russell (1998) developed Autoregressive Conditional Duration (ACD) model aimed at capturing the dynamics of irregularly spaced transaction data. This model spawned several extensions and applications over the last two decades.

The main concept behind ACD is studying the time that elapses between successive events in the financial markets. The event can be defined in a number of ways. In the context of a stock exchange, the most obvious one is the trade transactions where the trade duration models the waiting time between successive buy/sell activities in each stock. Engle and Russell (1998) state that one of the most important features of this high frequency trade data is that it is irregularly spaced in time. They treat the arrival times of trades as a marked point process. The stochastic properties of this peculiar process allow one to specify different distributions such as Exponential, Weibull or Gamma to model these ACD structures. As will be confirmed in this study later, the flexibility and the versatility of the Weibull distribution becomes useful in modeling the irregularly spaced duration data between consecutive trades (Meitz & Teräsvirta, 2006).

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Duration is widely recognized as a key measure for the elusive concepts of liquidity and illiquidity in financial markets. Cobandag-Guloglu and Ekinci (2022) provide a comprehensive review of liquidity measures in the high-frequency domain, categorizing duration as one of the main liquidity metrics alongside spread, quantity, and ratio. Unlike other forms of liquidity metrics that rely on periodic aggregation of data with fixed time intervals, duration-based models leverage irregularly spaced observations. This makes them particularly effective in capturing the intricate microstructure of financial markets, where trade timing often reflects the underlying liquidity conditions.

Ekinci (2008) highlights duration's resilience in modeling clustering in trade data, arguing that it is superior in documenting phenomena such as trade clustering, which traditional time-aggregated models fail to capture. While Ekinci (2008) notes that the complexity of duration-based models may pose challenges, this complexity is offset by their ability to provide granular insights into trade dynamics and liquidity. Duration modeling also extends its relevance to explaining volatility and higher moments of returns. Aldrich et al. (2014) demonstrated that inter-trade durations contribute to leptokurtosis and volatility clustering in clock-time returns, reinforcing the empirical relationship between duration and market volatility.

As financial markets become increasingly dominated by high-frequency traders (HFTs), the importance of intraday and high-frequency liquidity measures, such as those provided by ACD models, grows significantly. Aquilina, Budish, and O'Neill (2022) highlight that HFTs compete in a millisecond-level "arms race" to execute trades faster than their competitors. In this environment, traditional aggregated liquidity measures fail to capture the rapid, nuanced liquidity and volatility dynamics that HFT activity generates. ACD models, by contrast, are uniquely suited to analyze these dynamics due to their ability to directly model trade timing and duration with precision.

One of the primary reasons ACD models outperform other methods is their ability to treat trade arrival times as a marked point process, as introduced by Engle and Russell (1998). This unique approach enables ACD models to account for the stochastic nature of trade durations and link these to intraday liquidity and volatility dynamics. Unlike GARCH models, which focus solely on price volatility, ACD models provide an additional dimension by directly incorporating the time intervals between trades. This allows for the simultaneous modeling of trade timing, liquidity, and volatility, making ACD models particularly well-suited for high-frequency data analysis.

The ability to incorporate flexible distributional assumptions—such as Exponential, Weibull, or Gamma distributions—further enhances the adaptability of ACD models to different market structures (Meitz & Teräsvirta, 2006). For example, the Weibull distribution has been shown to effectively capture the irregular spacing of trades, offering flexibility that is critical in emerging markets like Turkey, where trading patterns often deviate from those in developed markets. Additionally, ACD models are uniquely positioned to reveal higher-order market dynamics, such as the relationship between transaction costs, market efficiency, and trade duration.

From a practical perspective, ACD models offer valuable insights for market participants. High-frequency traders (HFTs) can use duration-based metrics to identify liquidity and volatility dynamics that are invisible to traditional metrics, thereby improving trade execution strategies. Asset managers, on the other hand, can integrate ACD-based duration measures as complementary liquidity proxies in their asset pricing models, enabling them to optimize portfolio rebalancing strategies throughout the trading day. Regulators may also find ACD models invaluable, as they can document liquidity risks and transaction costs in real-time, providing a basis for informed policy decisions during periods of market instability.

The main motivation behind this study stems from the idea that trading times carry significant information, providing unique insights into market mechanisms and intraday liquidity. This study aims to model the arrival times of trades in the Turkish stock market, Borsa İstanbul (BIST), to shed light on its market microstructure and liquidity dynamics. By employing ACD models, this study seeks to identify which model specifications best capture the transaction durations in BIST and to document liquidity trends across a range of stocks. These contributions align with the broader advantages of ACD models, particularly their capacity to document the temporal dynamics of liquidity with a level of granularity and precision unmatched by alternative methods.

Borsa Istanbul is relatively large and globally well-connected financial market, making it a good candidate to study among its emerging market peers. Its standing among the global exchanges in terms of key statistics makes it even more interesting case. Among 90 exchanges that are members of World Federation of Exchanges, Borsa Istanbul ranked as 33rd in market capitalization, 24th in trading volume and 15th in number of trades, and 3rd in share turnover velocity during our study period of

2019[1]. As a measure of liquidity, share turnover velocity ranking puts BIST on par with the largest markets in the US and China. 64.71% of the tradable shares in BIST were held by foreign institutional investors at the beginning of our study period of October 2019[2]. Furthermore, Borsa İstanbul consistently ranks high on the list of most volatile markets in the world, being 5th in 2019 along with smaller and particularly unstable emerging markets[3]. This confluence of volatility and liquidity is puzzling, making BIST a market that demands a closer look into liquidity dynamics.

There are two major contributions to the financial literature that we propose in this study. Firstly, to the best of our knowledge, our study will be the first in-depth ACD application in Borsa İstanbul on multiple stocks in more than two decades. Only example of duration studies in Turkish market we could find is Şahin (1999), who applies ACD model on a single stock in an unpublished dissertation. As the markets have taken strides in speed and technology since then, we believe this study would help our understanding of the microstructure and intraday liquidity in the modern stock market. Secondly, the ACD literature does not offer any formal framework for error term distribution selection for high frequency duration data. In this study, we propose a framework on how to decide on the specifications by examining quantile-quantile plots, hazard functions, diurnally adjusted trading duration patterns for different time horizons, scatter plot of residuals against estimated conditional means, auto-correlograms and AIC/BIC comparisons for four different error term distributions. We also hope that this study will pave the way for further studies in the field, deepening our understanding of the local dynamics.

Our ACD model verifies the general pattern of these classical models but goes above and beyond them in documenting the intraday dynamics of liquidity and trading. None of the existing studies delve into irregular observations in 1-second granularity and time dimension of liquidity as we do with ACD modelling. They rely on flow of trades, orders or spreads across fixed time, losing valuable data in aggregation. In contrast, ACD model offers the opportunity to estimate next transaction arrival time on a second or even sub-second level. The calibration of the model offers the chance to model stochastic properties of liquidity measured in time. Beyond the scholarly contribution to understanding BIST market microstructure and liquidity, our results would be particularly useful for algorithmic and High Frequency Traders as they would be interested in understanding clustering of transactions and estimating the arrival of each trade.

The main framework of the study starts by selecting ten most traded stocks in our sample of intraday order book data of BIST securities. Following Engle and Russell (1998), we first "diurnally adjust" the data to eliminate the intraday periodicity that is constant. We then apply the ACD estimation on our diurnally adjusted durations for four different types of error term specifications that are commonly used in the ACD literature. Our aim is to be able to decide on which distribution is best for this market. Finally, we apply and document the results of the best fitting model for the ten stocks studied. The discussion follows with the implications and comparison with the model outcomes in other markets.

LITERATURE REVIEW

Conventional econometric models that are based on fixed time interval analysis fall short when operating in the intraday high-frequency domain, since transaction data appears in irregular time intervals. Enabled by improved automation of financial markets and advancements in computer capacity, including intraday high-frequency data in liquidity and volatility models have become necessary. In two different studies, Engle (2000, 2002) shows that the ACD model shares many characteristics with the GARCH models and that the durations can be modeled like volatility. ACD model of Engle and the GARCH model of Bollerslav (1986) share several mutual features, and both rely on economic incentives arising from the clustering of events and news in markets.

Building on the baseline model of Engle and Russell (1998), many researchers contribute to the literature by generating different types of ACD applications depending on their datasets and purposes. In the literature, there is a shared acknowledgment that the ACD models can be classified into three different generations. Exponential ACD (EACD), Gamma/Generalized Gamma ACD (GACD/GGACD), and Weibull ACD(WACD) can be considered as the most prevalent versions of ACD models that make use of different types of error term distributions since the model's inception. Models using Engle and Russell's baseline ACD with various error term specifications are classified as first-generation ACD models with the

1 Source: The World Federation of Exchanges (WFE) Statistics Portal. https://statistics.world-exchanges.org

2 Source: Central Securities Depository of Turkey Data Analysis Platform. https://www.vap.org.tr/yerli-yabanci-pay-senedi-analizi

3 Source: The Global Economy. Stock price volatility, percent, 2019 - Country rankings. https://www.theglobaleconomy.com/rankings/Stock_price_volatility

assumption of having the innovations following a distribution with non-negative support.

Developing on the first-generation models and addressing the needs for additional flexibility of parametric and nonparametric extensions, there are significant amounts of studies expanding the standard ACD model for improved versatility. Box-Cox ACD (BCACD) model of Dufour and Engle (2000), the logarithmic version (LACD) of Bauwens and Giot (2000), threshold implementation (TACD) of Zhang et al. (2001), and augmented modeling (AACD) of Fernandes and Grammig (2006) can be referred as these second-generation of ACD models. Pacurar (2008) delivers a comprehensive review of these first and second generations of models that were developed prior to the global financial crisis. She concludes by declaring that the group of ACD-GARCH models, along with the connection between price durations and volatility, may help develop risk measures based on transaction data that are beneficial for active intraday traders. While some studies have already been introduced, she believes this subject would be given further attention. Persistence in durations with Fractionally Integrated ACD (FIACD) of Jasiak(1998), asymmetric news impact curves with LACD models of Bauwens and Giot (2000), regime-switching models of Zhang et al.(2001), and latent factor-based models of Bauwens and Veredas (2004) are all assessed as having a rich potential of specifications and methods of estimations in the existing literature.

With the growing popularity of HFTs, recent developments in the duration models, and issues on capabilities and effectiveness of specific extensions of second-generation models, Hautsch (2012) provides an extensive survey and compilation of ACD models and their special cases. He presents different styles of ACD models and illustrates their effectiveness and capabilities in different types of applications. Starting with the standard ACD model of Engle and Russell (1998) and extending the model for specific purposes, the special cases are presented as; Additive and Multiplicative Model (AMACD) for incorporating news impact curves, Box-Cox Model (BACD) for concave and convex news impact functions, EXponential Model (EXACD) of Dufour and Engle (2000) for capturing piece-wise linear impacts, Hentschel Model (HACD) by Fernandes and Grammig (2006) for introducing multiplicative stochastic component and Spline News Impact Model (SNIACD) by modeling the news response.

The most recent literature on conditional duration models is classified as third-generation models that address the possible shortcomings and potential misspecification of the assumptions of the improvements. The semiparametric specification (SEMI-ACD) of Saart et al. (2015) proposes the semiparametric functional form procedure by using two separate components; first, a semiparametric time-series method for dynamics of duration process, second, an estimation algorithm for generating conditional durations that are only observable in lagged innovations. Another interesting class of ACD models can be assessed as Stochastic Conditional Duration (SCD). The models are based on the idea that a dynamic stochastic element drives the progression of durations. Gaussian SCD (IG-SCD) of Balakrishna and Rahul (2014) and Multiscale SCD (MSCD) of Men et al. (2016) can be presented as models for capturing random flow of information with the dynamic stochastic form. Moreover, Thavaneswaran et al. (2015) further describe these properties and introduce the class of generalized duration models using simulated dataset and recursive estimations. Bhogal and Variyam (2019) review this most recent literature on conditional duration models. Per the authors' statement, their study can be considered as an extension to Pacurar's (2008), where she studied the majority of the first and second-generation models of conditional durations. They review the theoretical and empirical studies developed after 2008 and the third-generation conditional duration models from the ACD literature. These state-of-the-art ACD models include nonlinear, time-varying, and semi-parametric autoregressive conditional duration models. SCD models studied by Men et al. (2015, 2016), which assume of having a dynamic stochastic latent variable as the driver of the evolution of the durations, are offered as having much scope for future research by the reviewers.

There are also remarkable empirical works on how to estimate and forecast features of the financial markets by using ACD models. Tse and Yang (2012) and Aldrich et al. (2014) predict the intraday volatility of equities using ACD models. Pyrlik (2013) delivers predictions on market crashes by using a similar methodology. Huptas (2014) develops an empirical study on trade durations of selected stocks in the Polish stock exchange by using Bayesian inference on ACD models. Li and Xing (2022) apply a similar approach to model quote volatility in a high frequency setting. The recent popularity of cryptocurrencies motivated a considerable effort on understanding the properties and microstructural behavior of crypto markets. Dimpfl and Odelli (2020) use ACD models to estimate the probability of a significant price event in Bitcoin and investigate how Bitcoin features are associated with durations and volatility.

Recent advances in ACD modeling have significantly expanded its theoretical and practical applications, with a focus on tail behavior and industry relevance. Cavaliere et al. (2024) provide groundbreaking insights into the role of tail behavior in ACD models, demonstrating that the asymptotic properties of maximum likelihood estimators are sensitive to the distribution's tail index. This finding is critical for robust inference and highlights the unique challenges posed by high-frequency financial data, particularly in cases where the number of events within a given time span is random. Similarly, Aquilina et al. (2022) explore the implications of high-frequency trading dynamics and latency arbitrage, revealing how modern market microstructure impacts liquidity costs and trading efficiencies. Their study emphasizes the potential of ACD models to capture nuanced market behaviors, such as the clustering of trades and their effects on liquidity and volatility. Together, these works underline the importance of incorporating sophisticated ACD frameworks in both theoretical research and industry practice to address the increasingly complex dynamics of global financial markets.

Despite the growing interest in high-frequency trading, studies on ACD applications in emerging markets remain relatively sparse, particularly in capturing the unique liquidity and volatility patterns distinct from developed markets. Bowe, Hyde, and McFarlane (2013) introduced an augmented ACD model in the Mexican derivatives market, showing that duration between transactions significantly influences price discovery, with liquidity considerations dominating information asymmetry in shaping trade timing. More recently, Li et al. (2024) applied a stochastic conditional duration (SCD) model to China's stock index futures market, demonstrating that price duration has a negative effect on both returns and volatility, a finding that contrasts with results from developed markets, where shorter durations typically amplify return volatility. However, beyond these few examples, the literature on ACD models in emerging markets remains limited, leaving significant gaps in understanding how microstructure conditions, regulatory frameworks, and market liquidity affect trade duration dynamics in less developed financial environments. The distinct intraday duration trends observed in emerging markets suggest that ACD models hold promise for capturing these nuances, yet more empirical research is needed to establish comprehensive frameworks applicable to diverse market conditions.

There is a limited number of studies documenting intraday dynamics in Borsa İstanbul. Even though they are not focused on liquidity or duration, there are some earlier studies which document intraday patterns in Borsa Istanbul. Bildik (2001) investigates the seasonality by the return and volatility of the equity prices, and reports a U-shaped pattern for price, a L-shape pattern for volatility and a significant intra-day seasonality. Küçükkocaoğlu (2008) shows the possible close end price manipulation caused by big buyers and sellers by examining the intraday return patterns. Also, by studying on the intraday returns and volatilities, Kadıoğlu and Küçükkocaoğlu (2015) compare the results of different market rules implemented by BIST administration in 2007 and 2012, they report a U-shaped intraday return for trading sessions and L-shaped intraday volatility patterns by examining the consequences of altered market conditions.

In studying intraday liquidity dynamics in an earlier effort for Borsa Istanbul, Ekinci (2008) documents a single stock's intraday liquidity in volume, number of orders and average order size. Karahan (2012) analyzes intraday trading activity for a large selection of stocks and Köksal (2012) delves into spreads and volume as liquidity measures. These studies find a common intraday pattern for the classical liquidity measures based on fixed intervals of 5 minutes. Gülay (2022) uses intraday number of trades and average order size to document liquidity's relationship with volatility. Sensoy (2019) constructs intraday limit order book to compute Xetra Liquidity Measure (XLM) and documents commonality in bid and ask sides of liquidity. As previously stated, Şahin (1999) is the only study on trade duration dynamics in Borsa Istanbul as he documents ACD model on a single stock in an unpublished dissertation. Our study will be the first of its kind in local duration dynamics in more than two decades in a cross-section of stocks.

MARKET and DATA DESCRIPTION

Borsa İstanbul commenced its trading in 1986 and has been active for both foreign and local investors since then. Trading activities moved to a fully computerized system in 1994. Although trading hours have changed a number of times throughout its history, the exchange operates without a break five days a week from 10:00 a.m. to 6:00 p.m. in its latest form including the study period. For each trading session there is a pre-auction session from 9:40 to 9:55 and a post-auction session from 6:00 p.m. to 6:10 p.m. During the continuous trading period, orders can be submitted canceled or modified without any limitation. If there is a presence of the counterparty, every single trade takes places whenever the related price and amount is met. The minimum trade amount is 1 share, and the minimum price variation is 0.01.

Table 1: Share of selected 10 stocks in the main trading statistics

Selected 10 Stocks' Share	Total Traded Value	Total Traded Quantity
in BIST 30 Index	76.03%	67.71%
in BIST 100 Index	59.01%	45.18%
in All Shares	47.69%	39.15%

Notes: This table contains shares of selected 10 stocks in the market's main trading statistics during the analysis period of October 2019.

Table 2: Descriptive statistics for our sample of 10 most traded stocks

	Price	Duration	Volume	Ask	Bid	Price	Duration	Volume	Ask	Bid
			BIMAS					KCHOL		
N	124580	124580	124580	124580	124580	133892	133892	133892	133892	133892
mean	47.791	4.851	13331	47.801	47.766	18.430	4.512	12236	18.437	18.421
max	59.55	831	127000000	49.86	49.84	21.54	469	11400000	19.44	19.43
min	36.8	0	39	46.06	46.02	14.37	0	15.08	16.95	16.88
sd	0.880	14.849	361243	0.833	0.833	0.547	14.737	43915	0.542	0.544
			EKGYO					PETKM		
N	157016	157016	157016	157016	157016	256741	256741	256741	256741	256741
mean	1.241	3.850	13701	1.245	1.235	3.486	2.354	17430	3.491	3.481
max	1.57	321	2480000	1.42	1.41	4.33	321	3406362	3.66	3.65
min	1.04	0	1.08	1.09	1.08	2.68	0	2.80	3.33	3.32
sd	0.073	9.854	69565	0.073	0.073	0.079	5.537	88311	0.079	0.079
			EREGL					SAHOL		
N	295448	295448	295448	295448	295448	169238	169238	169238	169238	169238
mean	6.647	2.046	13287	6.653	6.642	8.825	3.571	12288	8.831	8.819
max	8.28	324	2835849	6.99	6.98	11.1	339	6438474	9.68	9.67
min	5.17	0	5.26	6.43	6.42	6.63	0	8.18	8.18	8.17
sd	0.115	5.489	41513	0.111	0.111	0.347	10.286	35134	0.345	0.345
			GARAN					THYAO		
N	483272	483272	483272	483272	483272	896539	896539	896539	896539	896539
mean	9.381	1.251	38156	9.387	9.376	11.609	0.674	31126	11.615	11.603
max	12.02	323	28000000	10.28	10.27	14.85	321	20200000	12.4	12.39
min	6.68	0	6.68	8.25	8.24	8.6	0	8.60	10.6	10.59
sd	0.510	3.944	132348	0.508	0.508	0.395	2.091	106849	0.390	0.391
			ISCTR					TUPRS		
N	176486	176486	176486	176486	176486	284780	284780	284780	284780	284780
mean	5.954	3.423	17961	5.960	5.948	127.964	2.121	18244	128.029	127.902
max	7.38	395.00	8760000	6.34	6.33	169.6	322	14900000	143.8	143.7
min	4.48	0	4.48	5.49	5.47	94.9	0	97.00	117.4	117.3
sd	0.172	10.039	48192	0.169	0.170	7.491	6.205	70526	7.458	7.456

Notes: The table contains descriptive statistics for 10 most traded stocks' raw intraday transaction data for the analysis period of October 2019.

For this study, we acquired the intraday order book data from Borsa İstanbul of every single equity that is actively trading in the market for the month of October 2019[4]. The sample we select is comprised of 10 most traded stocks in BIST in terms of total volume during the study period. All 10 stocks are blue-chip stocks and members of headline BIST 30 Index. Table 1 reports the share of selected 10 stocks in trade statistics among the wider indices and the entire market. Ten selected stocks make up to 76% of the BIST 30 traded value, and 39-47% of the entire stock market in quantity and value traded. Hence, these 10 stocks make up a considerable portion of the trading. We also ensured that they do not possess any qualities that may bias the results. As recent index inclusion may inflate the trading volume, we checked that each stock has been in the index for at least the preceding three months. We also ensured none of the stocks has been hit with a circuit breaker within our study period. Circuit breaker is an exchange mechanism that stops trading in a security for minutes if certain conditions, such as exceeding price change thresholds, are met. Any such circuit breaker, if triggered, would bias the duration results.

The selection of the most widely traded stocks as our study sample allows us to use a comparable ACD model specification across all of them with a common time frame. This allows us to document intraday duration patterns for all 10 of them with some cross-sectional difference that will be documented in subsequent sections. Small and medium cap stocks have more sparse

[4] Source: Borsa İstanbul DataStore. https://datastore.borsaistanbul.com

data during the day, which causes problems in model calibration. Therefore, we chose to limit our data to these 10 stocks and document intraday dynamics, as is the standard in most of the literature.

The raw order book data records the entire order flow for each security. We eliminate orders and keep only realized transactions with a valid deal id along with security id, date, time stamp, price, volume, bid price and ask price information. All the transactions happening at the same second are aggregated in volume and volume-weight averaged in price. Ignoring sub-second data is standard in ACD literature as a large set of data in sub-second scale would pose problems in model calibration. We only keep the data from continuous trading sessions, eliminating all transactions that are timestamped before 10:00 a.m. and after 6:00 p.m. Table 2 demonstrates the summary statistics of 10 stocks in our sample based on raw data before 1-second aggregation.

After our selection and filtering process, the subset of 10 most traded stocks leaves us with around 3 million observations over 19 trading days to be used in our models. Turkish Airlines (THYAO) is the stock with the highest liquidity with an average duration below 1 second. We demonstrate tests of the models on THYAO stock before we carry on our calculations on the remaining nine stocks.

METHODOLOGY

High frequency transaction data are irregularly spaced and the times of these events serve as the arrival times of a point process. We follow Engle and Russell (1998) in modeling the durations between market transactions as ACD model. Since price or volume events are associated with the arriving time, the mechanism can be labeled as a marked point process. The stochastic process of the ACD model adopts a series of time points $\{t_0, t_1, \dots, t_n, \dots\}, t_0 < t_1 < \dots < t_n$. If we call $N(t)$, the quantity of events occurred before the time t, the conditional intensity process can be written as

$$\lambda(t \mid N(t), t_1, \dots, t_{N(t)}) = \lim_{\Delta t \to 0} P\left(N(t+\Delta t) > N(t) \mid N(t), t_1, \dots, t_{N(t)}\right)/\Delta t \quad (1)$$

The function in equation (1) can be specified as a hazard function. Parameterized duration function is assumed as the conditional probability of transaction i, occurred at time t provided the duration among t_i and $x_i = t_i - t_{i-1}$ where is the marginal duration between two consecutive transactions. If we let ψ_i be the conditional expectation of i^{th} duration, it can be written as

$$E(x_i \mid x_{i-1}, \dots, x_1) = \psi_i(x_{i-1}, \dots, x_1; \theta) \equiv \psi_i \quad (2)$$

And the standardized durations of the ACD model can be evaluated

$$\varepsilon_i = \frac{x_i}{\psi_i} \quad (3)$$

as independent and identically distributed. This indicates that the conditional expected duration can capture all the temporal dependencies and that ACD is characterized by the description of conditional duration ψ_i and the distribution of ε_i. Engle and Russell (1998) shows that the recent p durations characterizes the conditional duration and that a conventional model of $ACD(p,q)$ can be described as

$$\psi_i = \omega + \sum_{j=0}^{p} \alpha_j x_{i-j} + \sum_{j=0}^{q} \beta_j \psi_{i-j} \quad (4)$$

where p and q are lag orders.

The specification of error term ε_i arranges the ACD models into different categories. Exponential and Weibull distribution are the two most utilized distributions of the error term ε_i. The preference of distribution in (3) influences the conditional intensity or hazard function of the ACD model. The flat conditional hazard function implied by Exponential distribution leads into refusal of duration clustering. As it is indicated in many empirical studies including Engle and Russell (1998), Dufour and Engle (2000), Feng et al. (2004), Lin and Tamvakis (2004), using a flat hazard function implied by Exponential distribution is limiting and can be simply omitted in empirical applications. The shape of the Weibull distribution leads into more flexible analysis and fits the idea of duration clustering which can even be seen in raw data.

For the Weibull distribution with parameters κ and γ, the hazard function can be described as $h(x) = \kappa^\gamma x^{\gamma-1}$ and the conditional intensity takes the form

$$\lambda(t \mid x_{N(t)}, \dots, x_1) = \left(\Gamma(1+1/\gamma)\psi_{N(t)+1}^{-1}\right)^{\gamma}\left(t - t_{N(t)}\right)^{\gamma-1}\gamma. \quad (5)$$

The two-parameter family is obtained by Γ being the function and γ being the Weibull parameter, which indicates an increasing or decreasing hazard function. Depending on the Weibull parameter being greater or less than one, the hazard function is either upward or downward slopping. The log likelihood of Weibull function decreases to the log likelihood of exponential ACD if the parameter is equal to one. These parameters are acquired by using maximum-likelihood estimation. Finally, the log likelihood function for Weibull ACD can be assessed as

$$\log L = \sum_{i=1}^{N(T)} \ln(\gamma/x_i) + \gamma \ln(\Gamma(1+1/\gamma)x_i\psi_i^{-1}) - (\Gamma(1+1/\gamma)x_i\psi_i^{-1})^{\gamma}. \quad (6)$$

Further exposition on the other distributions tested here is omitted for brevity. Interested readers are referred to Hautsch (2012) and references therein for details on Exponential, Burr, and Generalized Gamma distributions.

The strong intraday seasonality is a well-known characteristic of the high frequency data (Bollerslev & Domowitz, 1993; Andersen & Bollerslev, 1997, 1998; Beltratti & Morana, 1999). Engle and Russell (1998) state that greater trading activity at the opening and closing of the trading sessions leads into smaller durations between transactions, and that it can be linked to the investor's behaviors. Before proceeding into modelling of the durations, we decompose the intraday durations into deterministic and stochastic parts. This method of removing the intraday seasonality effects is originally employed by Engle and Russell (1998). The diurnally adjusted durations $\tilde{x}_i$,of the durations x_i and the expected duration θ_ψ is given by (7) and (8) respectively

$$\tilde{x_i} = x_i/\phi\left(t_{i-1};\theta_\phi\right) \tag{7}$$

$$E_{i-1}(x_i) = \phi\left(t_{i-1};\theta_\phi\right)\psi_i\left(\tilde{x}_{i-1},\dots,\tilde{x}_i;\theta_\psi\right). \tag{8}$$

Two sets of parameters that we stated in the function (5) are estimated by using maximum likelihood with a two-stage estimation method. First, we use a cubic spline function to remove the intraday effects of durations, then we utilize these diurnally adjusted durations in our ACD model.

EMPIRICAL RESULTS

Diurnal Adjustments

After aggregating the data for each second as previously mentioned, we apply cubic spline method to remove the constant intraday effect from all our selected stocks separately. In order to demonstrate the removal of the seasonality from the data, we report the detailed results on the most widely traded stock in our sample, Turkish Airlines (THYAO). We use 896539 transactions of THYAO to estimate diurnal factors both aggregated for the entire sample period (Figure 1) and each day of the week separately (Figure 2). A few interesting insights can be observed from the outputs in Figures 1 and 2. Durations are longer in the middle of the day or "lunch time" and shorter at the beginning and the end of the day when traders are more involved. We can also see that the durations tend to get shorter after 15:30 local time, which coincides with the most macroeconomic news announcements in the US and related pre-opening trading in the US stock markets. Ekinci et al. (2019) confirm that the US macroeconomic news announcements at 8:30 EST (15:30 local time) do indeed impact liquidity and other metrics in the Turkish stock market.

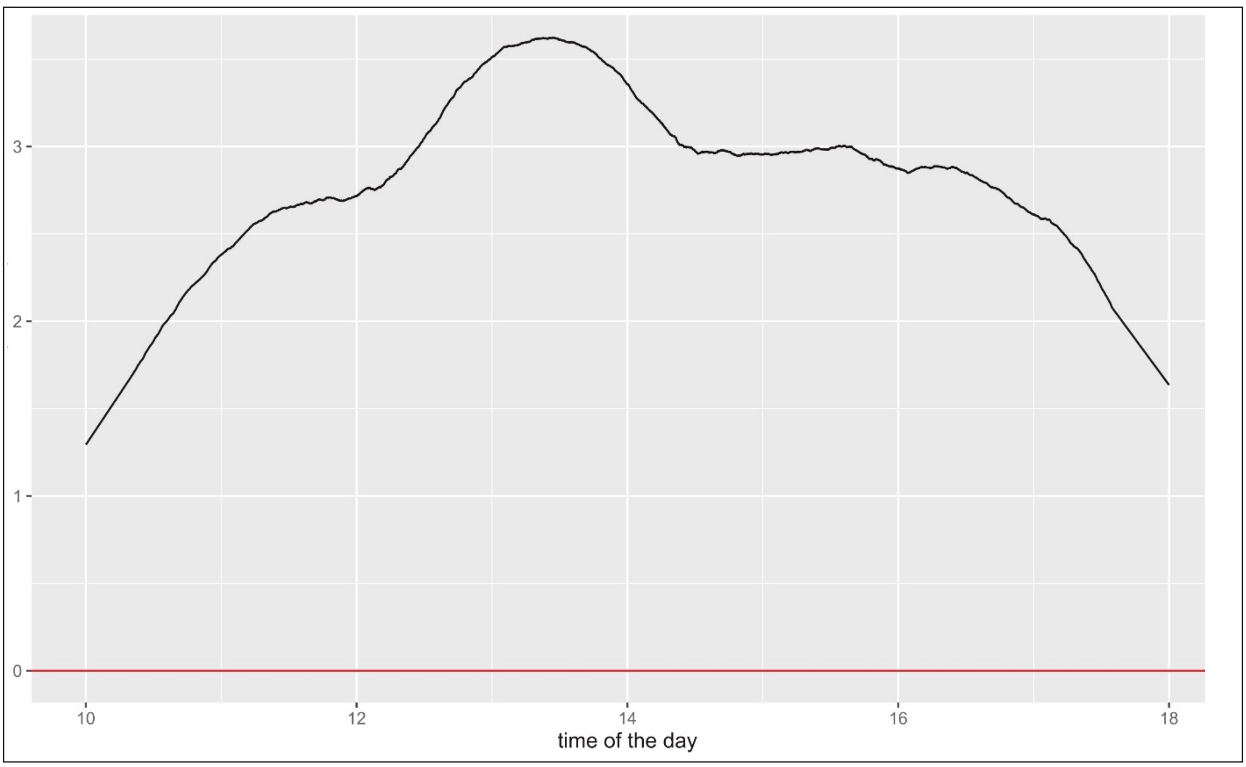

Figure 1: Diurnally adjusted transaction durations estimated by cubic spline function with daily aggregation

Notes: This figure shows intraday pattern for diurnally adjusted transaction duration for Turkish Airlines (THYAO), which is the most widely traded stock in our sample. Transaction data is aggregated for each second before diurnal adjustment. As expected, since trading activity is at its lowest at the middle of the trading session, the adjusted duration between the transactions are longest.

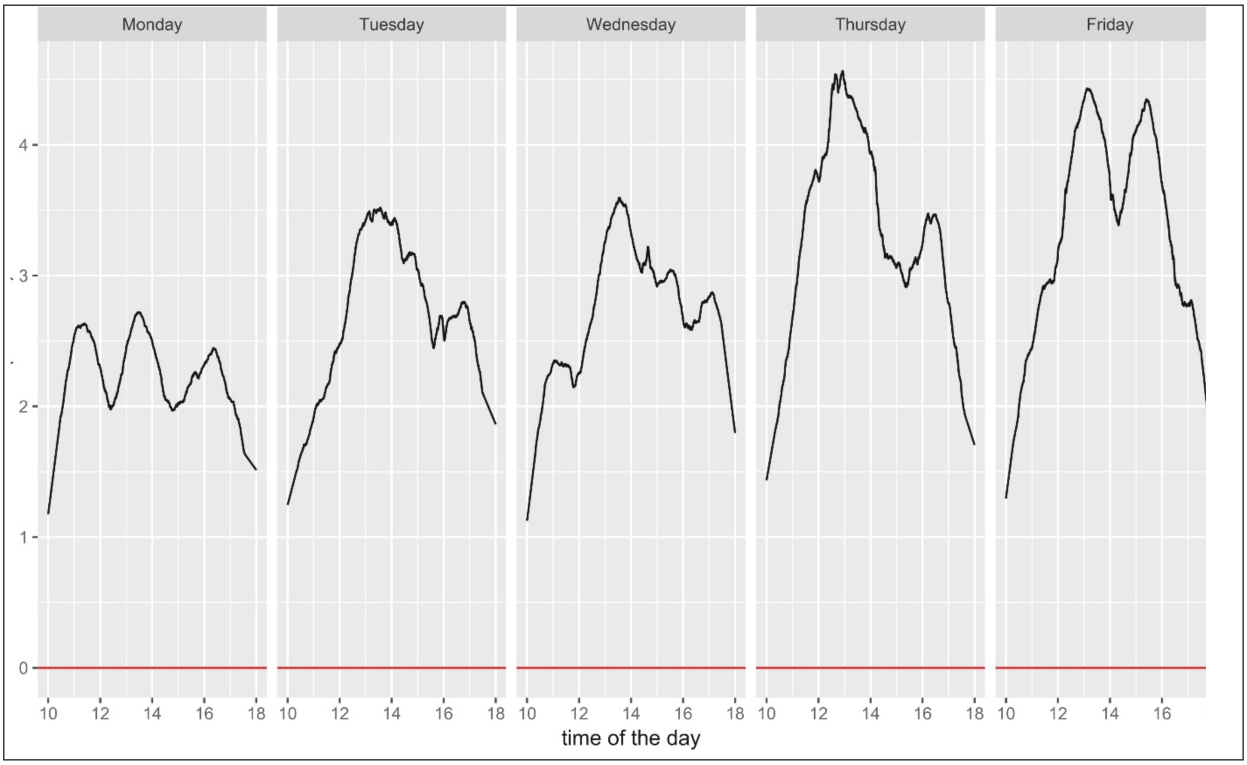

Figure 2: Diurnally adjusted transaction durations estimated by cubic spline function with day-of-the-week aggregation

Notes: This figure shows the results from day-of-the-week aggregation and plots the intraday duration patterns for each day of the week separately for Turkish Airlines (THYAO). Transaction data is aggregated for each second before diurnal adjustment. One can see that the intraday patterns are similar for each day with opening and closing activity higher than the rest of the day.

The patterns do not seem to differ vastly across days of the week. Unless one is interested in daily differences, there is no need to separate days of the week for their own diurnal adjustments. Unfortunately, the ACD literature has touched upon this issue too little to give us clear guidance. We continue with the intraday diurnal aggregation since we observe the same trading pattern with every equity in our sample.

As can be seen in Figure 3, diurnally adjusted durations are similar in shape across all of the equities in our sample. This similarity might be explained by the market-wide trading activity being parallel between different stocks or commonality in liquidity. High-frequency trading algorithms of the institutional traders and herding behavior among individual traders clearly add up to these clustering effects that we observe in durations. This clustering of events in time deserves attention in high-frequency analysis to be able to understand the microstructure of the market. Hence, this study contributes to the literature by documenting presence and dynamics of this phenomenon through the ACD results below.

Error Term Specification

For the second step of the maximum likelihood method, we fit diurnally adjusted transaction or trade durations of all stocks by using an as in the equation (8). In line with the literature, we use Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to verify the optimal lag length, and conclude that fits the data best. We chose THYAO again to further understand the differences among the choices of error terms distributions and clarify our selection of Weibull distribution in the rest of the study.

Exponential, Weibull, Burr, and Generalized Gamma distributions are the most used error specifications for capturing information from different types of financial duration data. We apply an model to THYAO data with these four different error term specifications and report the results in Table 3 and Figure 4. While Table 3 presents model fit criteria such as AIC, BIC, and MSE across four distributional specifications, it is important to interpret these results in conjunction with visual and diagnostic tools. Although Generalized Gamma occasionally delivers slightly better numerical fit metrics, it comes with added complexity due to its three-parameter structure, which can complicate estimation and interpretation—particularly across multiple stocks.

Consistent with prior literature (e.g., Meitz & Teräsvirta, 2006), we emphasize the value of using parsimonious and tractable distributions such as the Weibull,

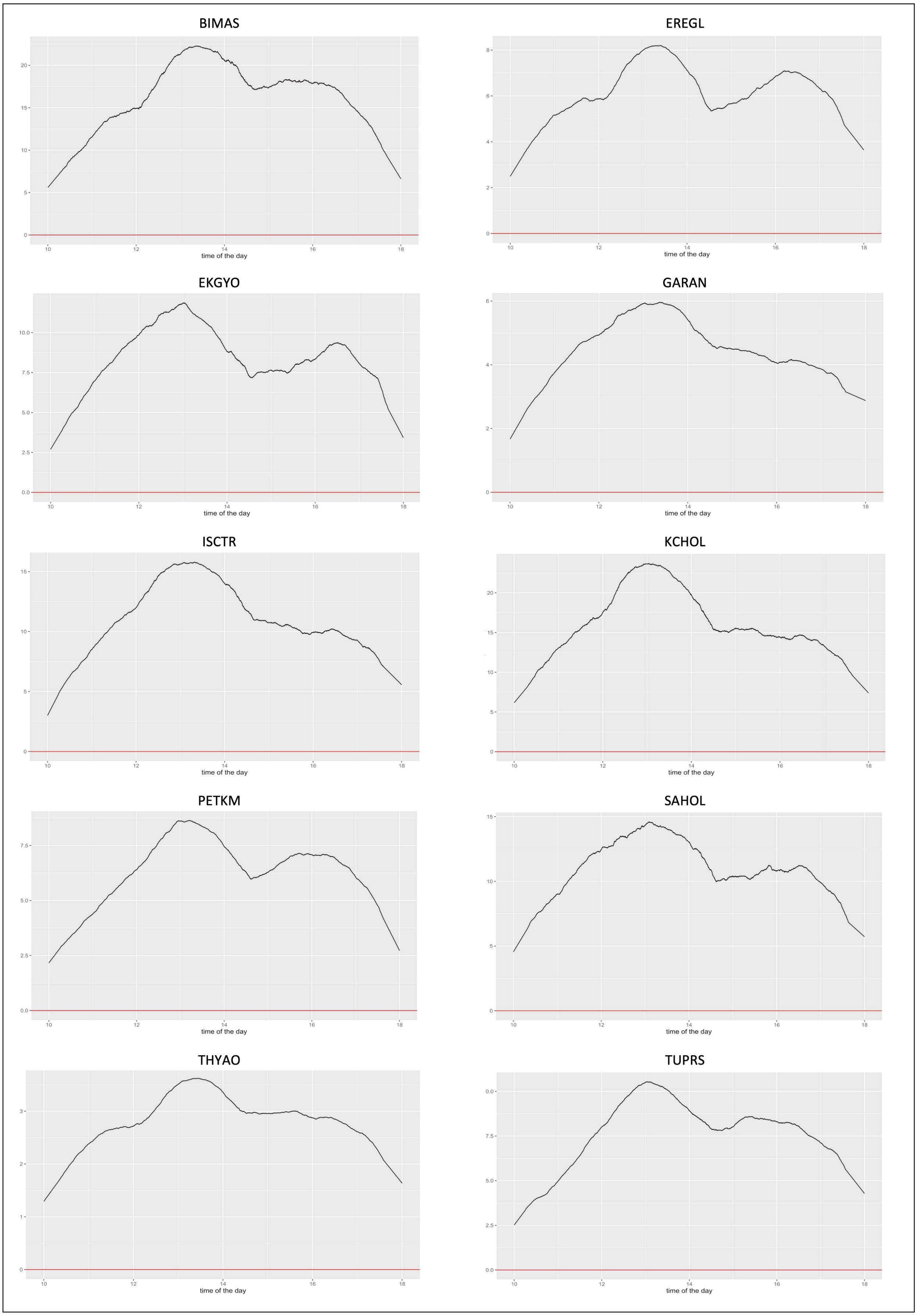

Figure 3: Diurnally adjusted transaction durations estimated by cubic spline function with daily aggregation for all stocks in our sample

Notes: This figure shows the diurnally adjusted transaction durations' intraday graphics for all stocks in our sample. Transaction data is aggregated for each second before diurnal adjustment. Intraday duration patterns and trading activity can be observed from the figures. The patterns are almost identical across all the equities.

which offer robust estimation properties and clearer interpretation of duration dynamics in high-frequency data. As further illustrated in Figure 4, the quantile-quantile plots show that both Weibull and Exponential distributions yield quantiles that more closely align with the theoretical expectations, especially in the tails. In contrast, the Generalized Gamma and Burr distributions exhibit noticeable deviations, suggesting potential misspecification in capturing the empirical tail behavior.

Taken together, the comparative diagnostic performance, model simplicity, and consistency with empirical precedent justify our decision to focus on the Weibull distribution for in-depth analysis, despite marginal differences in numerical fit in pooled results.

Another common method of assessing the closeness between theoretical distributions and empirical samples is through visual inspection of quantile-quantile (Q-Q) plots. In Figure 4, we report Q-Q plots for the four error distributions estimated for the THYAO stock. The sample quantiles are plotted against the theoretical quantiles, with deviations from the 45-degree line indicating mismatches between empirical and theoretical distributions. Consistent with the results in Table 3, the residual quantiles for the Weibull and

Table 3: ACD (1,1) application for 4 different distributions

	Coef	SE	PV	Goodness	Value		Coef	SE	PV	Goodness	Value
			Exponential						Weibull		
ω_1	0.0034	0.0003	0	LogLikelihood	-154261.0	ω_1	0.0034	0.0003	0	LogLikelihood	-163661.0
α_1	0.0801	0.0012	0	AIC	328582.1	α_1	0.0801	0.0012	0	AIC	327330.0
β_1	0.9189	0.0012	0	BIC	328836.9	β_1	0.9189	0.0012	0	BIC	327370.7
				MSE	1.0798	γ_1	1.3834	0.0022	0	MSE	1.0528
			Gen.Gamma						Burr		
ω_1	0.0284	0.0013	0	LogLikelihood	-99103.0	ω_1	0.0213	0.0018	0	LogLikelihood	-152064.9
α_1	0.1059	0.0024	0	AIC	298305.8	α_1	0.1185	0.0053	0	AIC	304209.9
β_1	0.8677	0.0027	0	BIC	298730.6	β_1	0.8666	0.0059	0	BIC	304549.6
κ_1	22.637	3.1064	0	MSE	0.9796	κ_1	1.1706	0.0095	0	MSE	1.0077
γ_1	0.1786	0.0125	0			σ_1	0.4389	0.0167	0		

Notes: ACD model is applied to transaction data of Turkish Airlines (THYAO), aggregated for each second and diurnally adjusted. All p-values are statistically significant. Goodness of fit values of loglikelihood, AIC, BIC and MSE are all reported.

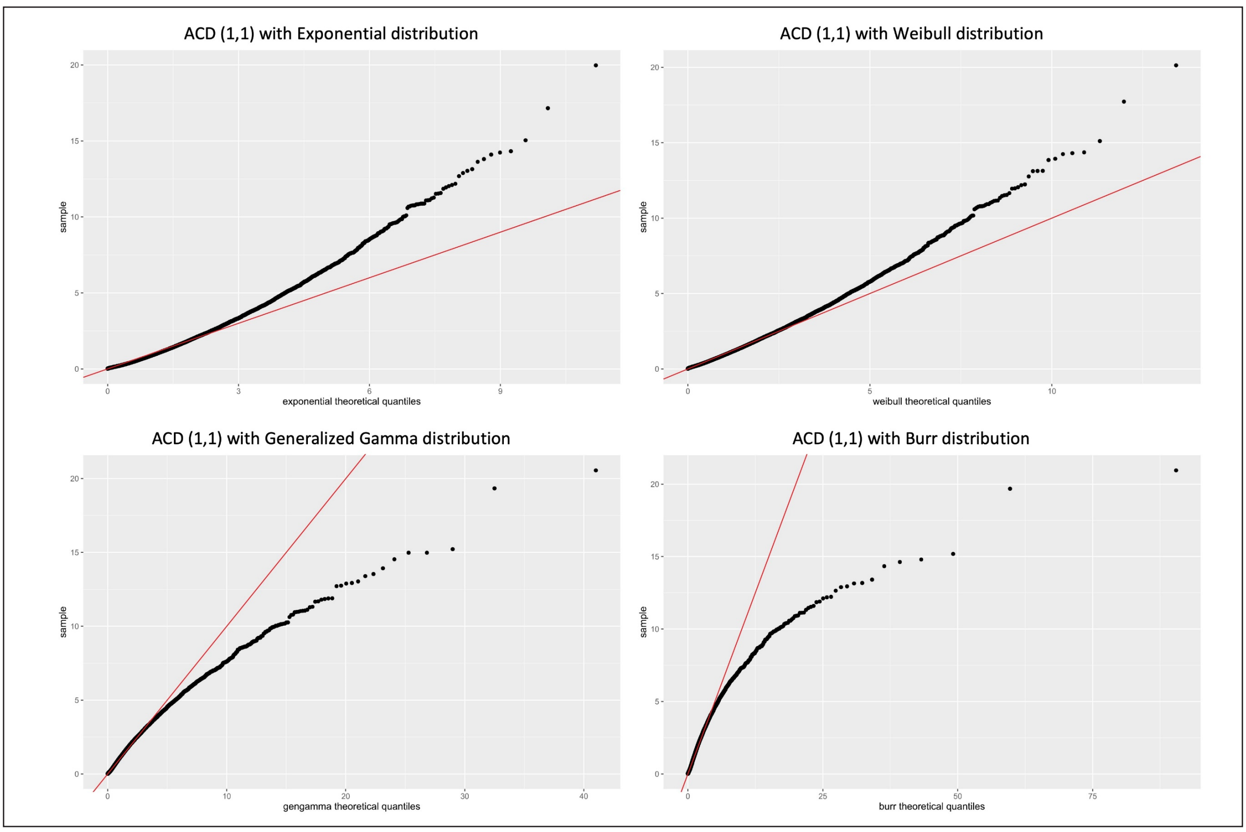

Figure 4: Q-Q plots for four different error term distributions; Weibull, Exponential, Generalized Gamma and Burr

Notes: This figure shows 4 different Q-Q plots for various error term distribution specifications for Turkish Airlines (THYAO). In the graphics, comparisons between theoretical and sample implied results can be observed and analyzed across different distributions for the most appropriate choice.

Exponential distributions align more closely with the theoretical quantiles, particularly in the tails. In contrast, the Generalized Gamma and Burr distributions show larger deviations, with the empirical quantiles falling below the expected line—suggesting heavier tails or distributional misspecification. These patterns reinforce the robustness of the simpler Weibull and Exponential models in capturing the underlying duration dynamics without overfitting.

When we compare the residuals with the estimated parameters of the selected error distribution, we can clearly determine that Weibull is a better fit for our sample. For the exponential distribution, the hazard function is flat and equal to one as the distribution is forced to have a unit expectation.

We also investigate how the estimated conditional means are predicting the mean size of the upcoming durations for the Weibull error term specification.

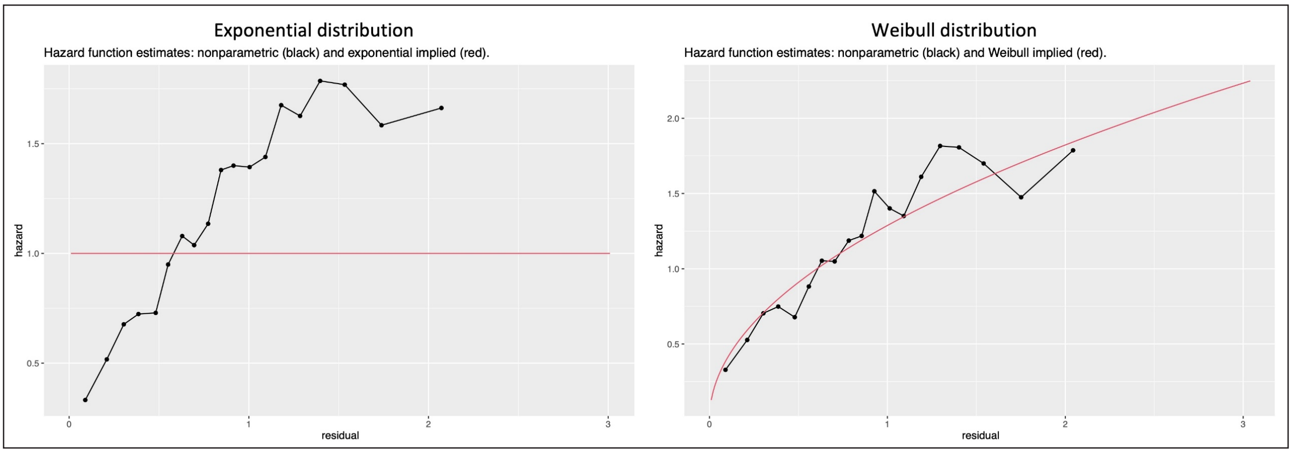

Figure 5: Hazard functions from the residuals estimated from ACD (1,1) with Exponential (left) and Weibull(right) error term specifications.

Notes: This figure shows 4 different Q-Q plots for various error term distribution specifications for Turkish Airlines (THYAO). In the graphics, comparisons between theoretical and sample implied results can be observed and analyzed across different distributions for the most appropriate choice.

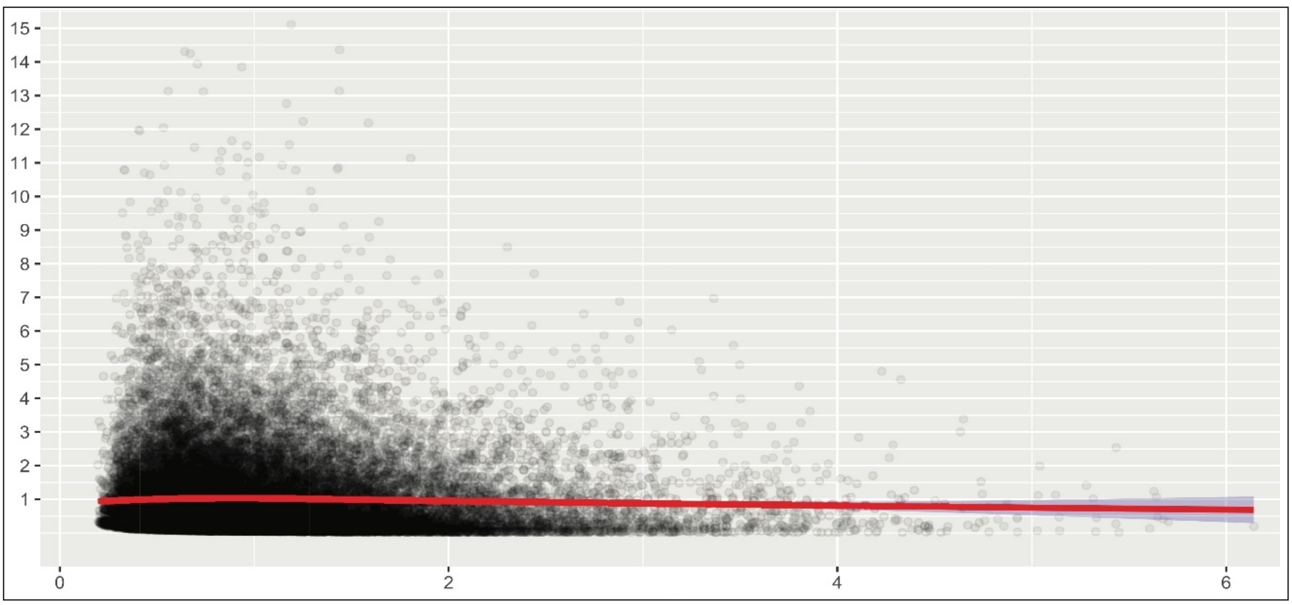

Figure 6: Scatter plot of residuals against estimated conditional means

Notes: This figure shows the level of the mean of the residuals which is expected to be the same across all values of conditional durations. The results are from WACD(1,1) model for Turkish Airlines (THYAO).

Figure 5 shows the hazard functions for Weibull and Exponential distributions to compare the results graphically. We plot both the non-parametric estimate of the hazard function from the residuals and the hazard function implied from the model estimate for THYAO.

Figure 6 plots the residuals and their mean against the estimated conditional means for THYAO. As is expected, the mean of the residuals is constant across each level of conditional durations.

ACD RESULTS

We use the Weibull error term specification for our ACD estimation of the 10 most traded stocks and report the results in Table 4. The computational results confirm the autoregressive component of the durations data. Table 5 shows the decreasing autocorrelation of durations due to the removal of diurnal components and ACD estimations. The autocorrelation behavior is similar across all the equities. The Weibull term is statistically significant at resolving the shape of the hazard function.

ACD with exponential specification when the Weibull parameter is equal to one. Engle and Russell (1998) report that all are less than 1 in their study of the US market and that this implies a downward slopping hazard function. We find that results of Weibull parameter slightly differ across separate stocks in our sample. We can explain these differences of coefficient levels by trading activity across markets and times. In the US market, the stocks had a higher sum of coefficients and and lower level of Weibull, since the institutional investors favored clustering and they are a lot more active compared to

Table 4: Estimates from the WACD (1,1) model applied to each equity in our sample

	Coef	SE	PV	Goodness	Value	Coef	SE	PV	Goodness	Value
			BIMAS						KCHOL	
ω_1	0.0227	0.0020	0	LogLikelihood	-33206.5	0.0167	0.0015	0	LogLikelihood	-32281.3
α_1	0.1042	0.0043	0	AIC	66421.0	0.0919	0.0038	0	AIC	64570.6
β_1	0.8749	0.0053	0	BIC	66455.0	0.8923	0.0045	0	BIC	64604.5
γ_1	0.9192	0.0039	0	MSE	1.7777	0.9163	0.0036	0	MSE	1.8955
			EKGYO						PETKM	
ω_1	0.0143	0.0008	0	LogLikelihood	-58006.6	0.0065	0.0004	0	LogLikelihood	-82597.6
α_1	0.1291	0.0030	0	AIC	116021.2	0.0707	0.0018	0	AIC	165203.2
β_1	0.8604	0.0032	0	BIC	116057.8	0.9242	0.0019	0	BIC	165240.9
γ_1	1.0197	0.0028	0	MSE	1.8691	1.1576	0.0028	0	MSE	1.23057
			EREGL						SAHOL	
ω_1	0.0095	0.0006	0	LogLikelihood	-81717.1	0.0083	0.0007	0	LogLikelihood	-45872.8
α_1	0.0832	0.0019	0	AIC	163442.1	0.0974	0.0029	0	AIC	91753.7
β_1	0.9091	0.0021	0	BIC	163479.7	0.8972	0.0031	0	BIC	91789.0
γ_1	1.1120	0.0027	0	MSE	1.3571	0.9950	0.0033	0	MSE	1.6559
			GARAN						THYAO	
ω_1	0.0077	0.0004	0	LogLikelihood	-108000.0	0.0034	0.0003	0	LogLikelihood	-163661.0
α_1	0.0933	0.0017	0	AIC	216299.4	0.0801	0.0012	0	AIC	327330.0
β_1	0.9016	0.0018	0	BIC	216338.4	0.9189	0.0012	0	BIC	327370.7
γ_1	1.1656	0.0023	0	MSE	1.5264	1.3834	0.0022	0	MSE	1.0528
			ISCTR						TUPRS	
ω_1	0.0146	0.0011	0	LogLikelihood	-48308.7	0.0070	0.0006	0	LogLikelihood	-69066.6
α_1	0.0936	0.0031	0	AIC	96625.3	0.0637	0.0018	0	AIC	138141.1
β_1	0.8933	0.0035	0	BIC	96660.9	0.9302	0.0020	0	BIC	138178.1
γ_1	1.0005	0.0032	0	MSE	1.5750	1.1120	0.0030	0	MSE	1.3187

Notes: ACD model is applied to transaction data for each stock in our sample, aggregated for each second and diurnally adjusted. The p -values for every coefficient are statistically significant at 5% level for each stock in the sample.

In Table 4, we can see the estimation outcomes. As it can be noticed, and coefficients are statistically significant, showing us a strong interrelationship in the transaction duration series. Since both coefficients are significantly greater than 0, it can be said that consecutive trades carry a high degree of dependence. The magnitude of the last duration can determine the timing of the next which leads into duration clustering. The persistence of transaction durations can be seen from the sum of and coefficients which is very close to 1. The current transaction duration is helpful in defining the next duration and this may possibly validate the duration clusters at a particular time of the day. The Weibull parameter for all stocks is also statistically significant.

The magnitude of Weibull parameter being greater or less than one tells us whether the hazard function is upward or downward sloping. The model reduces to the Turkish stock market. In contrast with the US market, we can see that the Turkish stock market has less trading activity and longer trade durations. As such, the findings in the US becomes a point of reference in interpreting the dynamics of a less developed market such as Borsa İstanbul.

Testing the Residuals

In order to investigate the validity of the ACD framework and test the possible autocorrelation of residuals, we use Ljung-Box Q-statistics, plot the correlograms, and Meitz and Teräsvirta's (2006) Lagrange Multiplier tests for ACD models. Test results are almost indistinguishable across all stocks in our sample. If the model is correctly specified, it is expected to have independent error terms, and the residuals should not show any further ACD structured dependency.

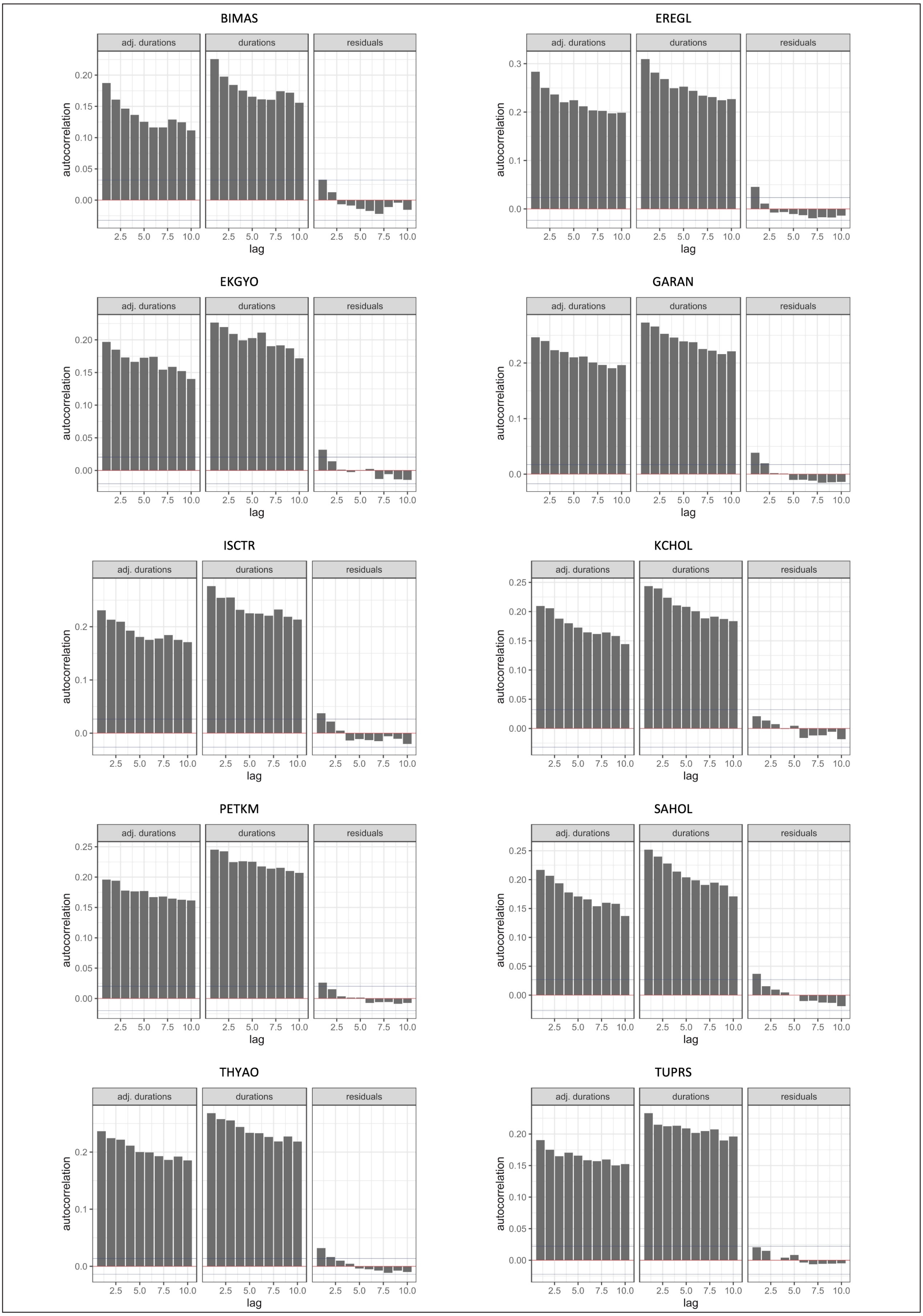

Figure 7: Auto-correlogram of durations, diurnally adjusted durations, and residuals for each stock in our sample

Notes: The figure shows the auto-correlogram for all stocks in our sample. It can be clearly observed that our WACD(1,1) model has approximately same results across different equities from Borsa İstanbul.

Table 5: Lagrange multiplier test of Meitz and Teräsvirta (2006) for no remaining ACD

Stock	L-M Stats	Degree of Freedom	P-value	# of durations
BIMAS	159	5	0	124580
EKGYO	212	5	0	157016
EREGL	261	5	0	295448
GARAN	423	5	0	483272
ISCTR	92.5	5	0	176486
KCHOL	124	5	0	133892
PETKM	228	5	0	256741
SAHOL	128	5	0	169238
THYAO	455	5	0	896539
TUPRS	125	5	0	284780

Notes: The results for Lagrange multiplier test of Meitz and Teräsvirta (2006) for ACD models to investigate possible remaining ACD Structure.

The null hypothesis that the residuals are autocorrelated is rejected, indicating that our model is accurately identified and fits the data reasonably well. It can be seen from Figure 7 that adjusted durations exhibit a strong autocorrelation structure, and the time of the day effect does not account fully for the dependence of the durations. model successfully removes the autocorrelation in the data. The residuals are not significantly autocorrelated. ACF is slowly decreasing to zero in all cases. We can further verify that there are no remaining ACD structures in the residuals from the M&T Lagrange Multiplier test, as shown in Table 5.

CONCLUSION

This study investigates and models the transaction durations in Borsa İstanbul on a sample of 10 most widely traded stocks. The durations from intraday order book data display strong auto-correlation; therefore, a general framework from conventional literature and a Weibull Autoregressive Conditional Duration model is used to inspect market microstructure and intraday liquidity dynamics. In addition, we provide a framework for choosing the error term specification by modeling the durations with different types of distributions that are most widely used in ACD literature.

Our analysis demonstrates that BIST durations can also be modeled successfully with respective methods by removing any autocorrelated dependencies parallel to the studies in the literature. Statistically significant and positive coefficients show that the durations are strongly interrelated and that they can be estimated by using past values of conditional and unconditional durations. Having a sum of the coefficients of past durations close to one reveals the strong persistence of lagged durations. The magnitude of the last duration can determine the timing of the next, and that leads to duration clustering. The information included in the conditional duration plays a more significant part in explaining the upcoming durations since is greater than in all cases.

Borsa İstanbul is one of the most liquid exchanges in the world measured by some measures. In fact, in 2021, Borsa İstanbul had the highest turnover velocity among all the members of the World Federation of Exchanges, a ranking it occupied the third place in our sample period of 2019[5]. This level of liquidity is reflected in average trade duration of stocks in our sample ranging from 0.67 seconds to 4.85 seconds. These statistics put the average trade duration in the same order of magnitude with the largest international markets like NASDAQ and Shenzhen Stock Exchange documented in the literature.

The ACD model has not been extensively employed to explain liquidity dynamics in Turkey's equity market, making this study a valuable contribution to the literature. Our findings align with some aspects observed in other emerging markets but reveal distinct characteristics specific to Borsa Istanbul (BIST). One of the key insights provided by ACD models is the shape of the hazard function, which captures the likelihood of observing a transaction immediately following a prior one. In China, Qi and Li (2013) report an upward-sloping hazard function, suggesting weaker serial correlation in durations and a more distributed arrival of trades over time. Similarly, Gurgul and Syrek (2016) identify an inverted U-shaped hazard function in Poland, reflecting market microstructure conditions distinct from developed markets. These findings contrast with the downward-sloping hazard functions commonly observed in the US stock market, where serial correlations are stronger, and transactions tend to cluster closely in time.

Parallel to the hazard function patterns reported in other developing financial markets, we find that BIST exhibits an upward-sloping hazard function, indicative of weaker serial correlation in trade durations and less likelihood of observing a transaction immediately following another. This suggests that, like other emerging markets, BIST

[5] Source: The World Federation of Exchanges (WFE) Statistics Portal. https://statistics.world-exchanges.org

is characterized by greater trade dispersion and less reliance on immediate market reactions. However, our findings also highlight important divergences. For example, Bowe et al. (2013) demonstrated that in Mexico's derivative market, trade timing is primarily liquidity-driven, influenced by market-maker obligations and institutional constraints. Similarly, Li et al. (2024) found that in China's stock index futures market, longer trade durations correspond to lower returns and volatility, which contrasts with the patterns observed in BIST, where high turnover velocity and volatility coexist, reflecting a hybrid microstructure between developed and emerging markets.

These cross-country differences underscore the importance of institutional, technological, and regulatory factors in shaping the dynamics captured by ACD models. The heterogeneous market structures across China, Mexico, and Turkey highlight the adaptability of ACD models in studying liquidity and trade durations across diverse environments. While our study contributes to filling the gap in the application of ACD models to Turkey's equity market, further research is needed to explore whether alternative duration models, such as stochastic conditional duration (SCD) models, provide a better fit for markets with complex liquidity and volatility dynamics like BIST.

The differences are also visible among the stocks in our sample. Although it consists of ten most widely traded stocks, even they display slight cross-sectional differences among themselves. The most frequently traded stocks in our sample, such as THYAO, GARAN, and EREGL, have their sum of and higher than other stocks, indicating the presence of the most enduring effects of their lagged values on the next transaction's appearance time. In contrast, the stocks with relatively less trading, BIMAS, KCHOL, and SAHOL, have the lowest sum levels signifying a weaker dependence.

The differences between emerging and developed markets, as well as among the stocks in our sample, may be explained by the differences in levels of liquidity, measured in trade intensity and lower durations. It can also be partly explained by trading activities of sophisticated traders like institutional, algorithmic and HFT traders. It is our conjecture that if the market participants are aware of intense trading, they take advantage of ample liquidity by trading more frequently causing stronger clustering. Borsa Istanbul, and other emerging markets, are relatively lacking in sophisticated traders, causing cross-country differences in intraday liquidity dynamics. Although HFT activity is rising in recent years in Borsa İstanbul, it is concentrated in the most liquid stocks, hence resulting in cross-sectional differences in our relatively limited sample.

The liquidity dynamics in Borsa İstanbul also impact the risk profile of the stock market. Being ranked as one of the most volatile stock markets in the world makes a market less attractive for investors. Hautsch and Jeleskovic (2009) argue that lack of liquidity causes future volatility in stocks in their study of high frequency dynamics. In an ACD setting, authors argue that trading intensity and clustering impacts volatility as well. Our findings point to a similar relationship, which requires further assessment of volatility dynamics and its relation with granular liquidity measures.

Our ACD results put the stochastic properties of trade duration in Borsa İstanbul in line with other developing countries. This finding lets us to conclude that although headline statistics like turnover and number of trades are high, sophisticated models like ACD provide more insight into actual liquidity dynamics. Borsa İstanbul liquidity, while seemingly on par with the most liquid exchanges, is not as robust as developed market exchanges when put under the microscope of a model like ACD. This finding confirms the need for a deeper analysis of market microstructure and trade clustering. This study is the second ever to study ACD models in Borsa İstanbul in more than two decades and first of its kind to do it in a cross-section of stocks. As trading speed increases and intraday dynamics become ever more important, we believe this study would initiate more interest in studying the market microstructure and intraday liquidity in Borsa İstanbul.

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