INTRADAY CORRELATION DYNAMICS IN BORSA ISTANBUL USING SCORE-DRIVEN KALMAN FILTERING

HULUSİ BAHCİVAN

BOĞAZİÇİ UNIVERSITY

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Hulusi Bahcivan

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DECLARATION OF ORIGINALITY

I, Hulusi Bahcivan, certify that

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- this thesis contains no material that has been submitted or accepted for a degree or diploma in any other educational institution.
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ABSTRACT

Intraday Correlation Dynamics in Borsa Istanbul

Using Score-Driven Kalman Filtering

Studies on intraday conditional correlation dynamics is limited and existing literature mostly depends on classical methodologies that are prone to errors due to unaddressed issues like non-synchronous trading and market microstructure noise. Trades are not homogenously scattered along the day. Hence, upon close inspection of data in high frequency domain such as one-second-long intervals, one sees intermittent and irregular observations. In contrast to its methodological counterparts, combination of Generalized Autoregressive Score (GAS) framework and State-Space Modelling produces reliable results on such data structures by guaranteeing full data usage. Findings of this study reveal that average intraday conditional correlation rises as trading commences, lingers around certain altitude for some time before an upward trend closes out the trading day, which we attribute to the US market opening. Visual inspection of the findings across different market conditions and days of the week reveals elevated correlation levels in volatile markets as well as a distinguishable path for both ends of a week. A closer inspection of findings via Dynamic Time Warping exhibits that intraday conditional correlation patterns are discernibly different for Mondays, Tuesdays and Fridays. Beyond the scholarly contribution, the methodology and findings are of interest to various parties like high-frequency traders, risk and portfolio managers and regulatory agencies in formulating their high frequency trading practices, margin requirements and portfolio construction schemes.

ÖZET

Skor-Güdümlü Kalman Filtresi ile

Borsa İstanbul'da Gün İçi Korelasyon Dinamikleri

Gün içi koşullu korelasyon dinamikleri üzerine çalışmalar kısıtlı olmakla birlikte mevcut literatür çoğunlukla, asenkron işlemler ve mikro yapı gürültüleri gibi göz ardı edilen hususlardan kaynaklanan hatalara açık klasik metotlara dayanmaktadır. İşlemler gün içinde homojen olarak dağılmamaktadır. Dolayısıyla, ilgili veri 1 saniye gibi bir uzunluktaki yüksek frekans düzleminde yakından incelendiğinde, ara sıra ve düzensiz sıklıkta gerçekleşen işlemler gözlemlenecektir. Benzer metotların aksine, Genelleştirilmiş Özbağlanımlı Skor modeli ile Durum-Uzay modelinin birlikte kullanılması var olan bütün bilginin kullanılmasını sağlayarak güvenilir sonuçlar üretilebilmektedir. Bu çalışmanın sonuçları, gün içi ortalama koşullu korelasyonun işlemler başladıktan sonra arttığını ve bir süre belirli seviyelerde seyrettikten sonra Amerika piyasalarının açılmasına atfettiğimiz yukarı yönlü bir trend ile günün tamamlandığını göstermektedir. Bulgular farklı piyasa koşulları ve haftanın farklı günleri için görsel olarak incelendiğinde, istikrarsız piyasa koşullarında korelasyon seviyelerinin daha yüksek değerlere ulaştığı ve hafta başı ile haftanın sonu için seçilebilir ölçüde farklı bir rota oluştuğu görülmektedir. Bulguların Dinamik Zaman Bükme algoritması ile daha yakından analizi, gün içi koşullu korelasyon davranışının Pazartesi, Salı ve Cuma günleri için ayırt edilebilir şekilde farklı olduğunu ortaya koymaktadır. Bilimsel katkının ötesinde, metodoloji ve bulgular; yüksek frekanslı işlem yapan yatırımcılar, risk ve portföy yöneticileri ve düzenleyici kurumlar için, yüksek frekanslı işlem alışkanlıklarının, portföy oluşturma şemalarının ve teminat gereksinimi hesaplamalarının şekillendirilmesi noktasında önem arz edebilir.

CURRICULUM VITAE

NAME: Hulusi Bahcivan

DEGREES AWARDED

PhD in Management, 2021, Boğaziçi University
Master's Degree in Financial Economics, 2012, Galatasaray University
BA in Economics, 2009, Boğaziçi University

AREAS OF SPECIAL INTEREST

Capital markets, money markets, asset pricing, risk management, portfolio management and econometric modelling.

PROFESSIONAL EXPERIENCE

Executive Assistant to CEO, Takasbank, Jul. 2020 - Jan. 2021
Senior Specialist, Central Counter Party, Takasbank, Jan. 2020 - Jul. 2020
Senior Specialist, Fund Valuation and Custody, Takasbank, Oct. 2017 - Jan. 2020
Senior Specialist, Equity Clearing and Settlement, Takasbank, Apr. 2015 - Oct. 2017
Senior Specialist, Financial Planning and Analysis, adidas Group, Oct. 2014 - Apr. 2015
Assistant Expert, Emerging Companies Market, Borsa Istanbul, Oct. 2010 - Jun. 2014
Management Trainee, Corporate and Commercial Credits, Garanti BBVA, Aug. 2009 - Jul. 2010

AWARDS AND HONORS

Highest Honors List, Boğaziçi University, 2021
Highest Honors List, Galatasaray University, 2012
Honors List, Boğaziçi University, 2009

PUBLICATIONS

Journal Articles

Bahcivan, H., (2020). Epps Effect still existent: Differing unconditional correlation behaviors for inter-sector stock pairs. International Journal of Disciplines Economics & Administrative Sciences Studies, Vol:6, Issue:24, pp:797-805 *to my family…*

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CHAPTER 1

INTRODUCTION

1.1 Correlation and investment decisions

> Some commentators and so-called "value" investors, who seek out undervalued stocks, have gone as far as to declare stock-picking dead. As one US fund manager says: "We spend all this time picking stocks and then everything rises and falls at the same time. It is a nightmare. Most active fund managers add so-called "alpha", or risk-adjusted returns, by focusing on earnings fundamentals and relative valuations. But rising correlation means that their work has gone unrewarded – stock moves have tended to be driven by sentiment about the direction of the global economy and little else.
> Anousha Sakoui and Izabella Kaminska, The rise and rise of correlation, Financial Times, October 6, 2010.

> J.P. Morgan equity analysts say that the highly correlated conditions in stocks represents a bubble likely to pop: "Correlations between stocks are currently at the highest level in recent history. This is a result of the macro environment, record use of index derivatives such as futures and to a lesser extent ETFs, and high-frequency trading.
> Matt Phillips, J.P. Morgan: There's a Correlation Bubble in Stocks, Wall Street Journal, October 8, 2010.

> Is stock picking a dead art? It has looked that way in recent weeks, as macro issues such as the solvency of European countries and fears of a global economic slowdown have overshadowed fundamental differences between companies. The consequence is that stocks are moving in tandem, indicating a high degree of correlation.
> John Jannarone, Traders Seek Salvation from Correlation, Wall Street Journal, August 29, 2011

Covariance dynamics has been one of the widely studied topics in the field of finance. Market participants ranging from portfolio and risk managers to individual traders have been keeping eye on the co-movement of assets especially in such an era of highly intertwined financial environment. Assets' hand-in-hand movement soars especially during market downturns and portfolios need to be formed wisely to evade these attacks unscathed. During times of elevated correlations, individual firms' fundamentals are superseded, and market-wide forces dominate pricing mechanisms. Although positive shocks bring about upward trend in correlation numbers in a similar fashion, Pagan and Schwert (1990) introduce news impact curves to depict that negative shocks cause more volatility; a finding which bears an implicit piece of advice for investors to be more particularly cautious for plunging markets. Investors are more likely to go through financial crises in recent decades: the world witnessed thirty-five crises in the last four decades, whereas the total number of crises was thirty-one for the preceding four centuries between 1600 and 1980 (Akgiray, 2019, p. 11).

Since the inception of Modern Portfolio Theory, it is well-known that correlation affects portfolio returns, yet it has come to occupy investors' minds comparatively more in the aftermath of the latest financial crisis. In lockstep with the practical questions arising on major finance hubs, academic literature rediscovered the impact of correlation on asset prices. How the returns of different securities co-move or diverge over time and accompanied implications for different investment horizons attracted considerable attention. Concurrent rise of high frequency trading (HFT) points researchers and practitioners towards examining the dynamics of asset prices on granular levels and gauge pricing mechanisms on a deeper level.

Markowitz (1952) assumes that investors are risk averse; they want to minimize the risk given a certain level of expected return. Going forward, he points out that -in terms of riskiness- holding two (or more) uncorrelated assets is superior to the strategy that puts all the funds to one single asset, which came to be known as diversification benefits. Given it is composed of uncorrelated or even correlated assets, variance of a portfolio can be lower than that of the asset with the minimum variance in the bundle. In that regard, Markowitz (1952) suggests a "right kind of diversification”. For instance, an investment decision that hoards stocks only from aviation industry will be vulnerable to shocks and will hardly provide the desired protection. Risk of a portfolio becomes more of a covariance risk whereas variance risk gradually fades as the number of constituents in a portfolio increases (Fama,1976, pp. 251-254). Recently, Krishnan et al. (2009) model correlation as a new asset pricing factor and conclude it to have a negative price. This implies that investors are willing to sacrifice certain level of return for protection against the risks associated with increasing correlation among assets. Longin and Solnik (2001) similarly present the related empirical findings for the periods of market crises; given the time-varying patterns in correlation, investors should be cautious about time-varying diversification benefits and they would be willing to pay some premium for the assets that perform well in states of higher correlation.

Modern financial markets require a deeper look into data in increasingly finer level, as certain group of investors keep their investment horizons very short; a day-long or even shorter. Silber (1984) and Kuserk and Locke (1993) show that intraday speculators’ inclination is towards closing their positions, not carrying it overnight. Hence, only in the case they are provided with some amount of compensation, namely a risk premium, these speculators will be keeping their positions until the next trading day. As is widely known by the stakeholders of finance community, trading business is highly computerized and trading floors have become symbolic. Changing investment practices along with the availability of mass amounts of data and unprecedented computing power have created a fertile ground to analyze the said data. Zhang (2010) estimates high frequency trading to constitute 78% of all trading volume in US capital markets. This figure is around 20% for Borsa Istanbul equity market.[1] Hence, accurate dynamic correlation measurement during the day is critical to decide on when to form a portfolio and when to unload accompanying positions for certain class of investors in this nascent subset of vast investment universe. Regardless of the unconditional correlation patterns, day traders are exposed to potential intraday risks and try to reap the rewards out of quite short-term movements. However, classical correlation measurement methodologies become misleading when the main focus is on increasingly shorter intervals. Epps (1979) shows that correlation magnitudes decrease as data analysis is conducted on shorter time scales; eponymously called Epps Effect in the literature.

In recent years, we witness an unprecedented technological improvement in almost every layer of trading activity. Breakneck speed in order transmission, matching engines processing thousands of different orders in just one second, nearly instant data dissemination, automated data processing tools, accelerated information flow, versatile disclosure channels, growing share of algorithms in trade volumes etc. are all indicators that very short-term investment horizons will be of greater importance than before and trading business is being visibly transformed to be the domain of machines rather than human portfolio managers. In other words, focusing on capillaries rather than the arteries of asset price formation can be fruitful especially in the years to come.

[1] Y. Gurak, Borsa Istanbul Technology Sales Manager, personal communication, January 27, 2021

1.2 Motivation

As is shortly stated, so as to reap the benefits of diversification, asset correlations must be watched with intense care. Studies on correlation may be divided into two different stages; first stage shelters the ones that assume a constant correlation among the assets while the second stage, which starts with Bollerslev et al. (1988), hosts studies of time-varying correlation among portfolio ingredients. More recently, Engle (2002) introduces various types of dynamic conditional correlations and measures their performances in different settings. Inter-asset correlations generally soar during market downturns; an occasion that is sure to cause market-wide panic and herd-behavior among investor community. In today's trading business, some investors are not holding overnight positions and they are after generating alphas out of quite short-term movements. In that regard, correlation between assets in highly short-term intervals can be used for profit generating purposes. Buccheri et al. (2020) introduce the combination of state-space model and GAS model to unearth conditional correlation patterns in shorter time scales. This is a model that alleviates the shortcomings of conventional tools in quantifying correlation dynamics at such short intervals.

This thesis will shed light on intraday correlation dynamics in Borsa Istanbul equity market by adopting the sophisticated approach in Buccheri et al. (2020) and will become the first study applied in an emerging market exchange. This will also be the first study which elaborates on day-of-the-week effect in conditional correlations and on diurnal correlation movements in chaotic market conditions. Outputs will serve as valuable hints for day-traders, risk and portfolio manager and clearing agencies as the findings elucidate dynamic conditional correlations for different days of a week and different sections of a day.

CHAPTER 2

LITERATURE

2.1 Epps effect

In 1979, Thomas Epps analyzed four different stock prices in the same industry to detect the very short run co-movement among them. Prices of AMC, Chrysler, Ford and GM that are taken from New York Stock Exchange were recorded with ten minutes intervals for the first half of 1971 and Epps calculated inter-stock correlations (of log price changes) for ten, twenty and thirty minutes, one, two and three hours and one, two and three days of intervals. His findings for the correlations of changes in the log prices were tabulated starting from the very short-term interval to three days and figures for the ten-minute intervals were the lowest among. Epps reached a revelatory conclusion that the correlations become quite low as the measurement interval gets shorter, whereas larger time steps yield larger correlation figures.

Non-concurrent trades and lagged reactions to same market news were the reasons behind Epps Effect. Although the narrowest time scale was ten minutes in Epps (1979), Budish et al. (2015) again visualize the Epps Effect with intervals even from 1 millisecond to sixty seconds. In other words, researchers are still doomed to correlation underestimation if they insist on classical estimation methods. Lo and MacKinlay (1990) also explain how lead-lag effect biases the econometric results. However, with recent breakthrough in technological infrastructure and advances in data processing, lagged reactions seem to be highly eliminated though not perfectly. For instance, Budish et al. (2015) present extremely shortened duration of arbitrage opportunities over years; an empirical finding that shows how the technology tremendously transformed trading business. In a nutshell, market responses to a newly released information seems faster than before. These advanced reflexes still do not cure missing values problems when the researcher is after the patterns on granular levels.

Fisher (1966) seems to be the first who analyzes non-synchronicity: non-contemporaneous price quotes during index calculations and its possible outcomes. Lo and MacKinlay (1990) touch upon frequency differences in trades of different stocks and build a stochastic model for non-synchronous asset prices. They take two imaginary stocks i and j, i being less frequently traded among investors. If some ground-breaking news reaches to market around closing hours, the price of j shows an immediate response due to being more liquid while asset i's price reacts to this information with a lag. There will be a typical lag affect and that will impel a cross-autocorrelation between the prices of i and j. Hence, a portfolio which includes both assets will have an autocorrelation too.

Bonanno et al. (2001) select one-hundred stocks from US equity markets for the period January 1995- December 1998 and construct a Minimum Spanning Tree (MST) and Hierarchical Tree (HT) by clustering the financial data on the basis of correlation coefficients. Having a correlation matrix in hand, they calculate a metric distance out of correlation coefficients and in a sense convert the numbers to visual presentations to utilize geometry and taxonomy. They first derive the results with a time span of 6 hours and thirty minutes (one day) and later shorten the interval to nineteen minutes and thirty seconds (one day/20). As the time horizon gets tiny, MST and HT figures become less complicated and mean correlation coefficients between the stock pairs decrease, more salient diminution being observed among the mostly correlated pairs; that is, intra-sector correlation figures decrease faster than those of inter-sector.

Reno (2003) likewise points out non-synchronous trading and lead-lag relationship to be the possible causes behind the statistical findings of Epps (1979). Reno (2003) aims to breakdown the individual impacts of these two alleged factors and seeks for other potential explanatory reasons. He adopts the Fourier method to complete his study; a method which enables him to use the data as it is without altering the time structure of tick-by-tick data. He makes the most of Monte Carlo simulations and hypothesizes that provided there is no lead-lag phenomenon and all the trades of two assets are simultaneous, there should not be any frequency related impacts in correlation measurements. He concludes those two factors are the main reasons of declining correlations with higher frequency and presents an evidence from his analysis on DEM-USD and JPY-USD exchange rates data. With simultaneous quotes, Epps Effect is eliminated to some extent although not completely eradicated. He calculates 8 seconds of lead-lag relationship in the data pair and reanalyzes his findings by shifting one of the data series 8 seconds to secure synchronicity. This operation substantially decreases the Epps Effect and makes him to assert non-synchronous trading and lead-lag relationship are the principal causes of Epps Effect. His analysis on two stocks -Mobil and Exxon- also gives similar results, lag period this time being seventy seconds.

2.2 Conditional correlation measurement

Univariate GARCH models due to Taylor (1986) and Bollerslev (1986) are handy in model construction, but multivariate GARCH models are more encompassing in the sense that they additionally involve covariance dynamics. There are several versions of it and Kroner and Ng (1998) present detailed explanation for interested readers. However, although conditional covariances can be time-varying, conditional correlations may be deemed constant as in Constant Conditional Correlation (CCC) model of Bollerslev (1990). Later, Engle (2002) proposes Dynamic Conditional Correlation (DCC) GARCH model to account for time-varying correlations. However, GARCH models have some shortcomings when the researcher is interested in high frequency patterns. As the measurement interval shrinks, GARCH outcomes become flawed due to non-synchronous data points. In other words, correlation numbers are biased downwards because of sporadic observations and dynamics are not captured accurately. Buchheri et al. (2020) compare alternative models in estimating conditional intraday correlations and DCC GARCH performs the worst among. Engle and Kelly (2012) introduce Dynamic Equi-correlations (DECO) in which they assume the correlations to be same across asset pairs for each estimation period. This parsimony provides easiness to estimate covariance matrices of larger dimensions and it is found to be performing better than DCC GARCH.

Malliavin and Mancino (2002) form a Fourier model in which the log-prices are assumed to be following a continuous diffusion process. They model time-varying volatilities and covariances whereas assume a constant correlation among asset returns. Hayashi and Yoshida (2005) adopt a model in which irregularly spaced observations are synchronized via deletion operations and they are criticized by Ait-Sahalia et al. (2010) because of the information sacrificed.

Tilak et al. (2013) use Hayashi-Yoshida estimator to depict intraday correlation. Their conclusion reveals an increasing average pattern as the time elapses throughout the day. However, applied method has some soft spots one of which is it involves data reduction during estimation. The model is also run on 5-minutes interval return series and has no recommendations for high frequency analysis. Allez and Bouchaud (2011) also discover a climbing pattern in correlation but model is again built on series where data points are 5 minutes apart.

In observation-driven models, a classification due to Cox (1981), time-varying parameters are updated via the scores of conditional log-likelihoods as shown in Buccheri et al. (2020), Della Monache et al. (2016), Creal et al. (2013), Creal et al. (2011). Generalized Autoregressive Score (GAS) model which is due to Creal et al. (2013) is a kind of observation driven perfectly deterministic model and movements in the time-varying parameters are steered by the calculated score at each time period. Here, score is simply the derivative of the joint density function of all available observations with respect to the time-varying parameters in question. These operations can be effortlessly incorporated with state-space modelling framework and derivation outcome can be expressed in prediction error decomposition form as presented in Buccheri et al. (2020), Creal et al. (2008) and Della Monache et al. (2016). As an ultimate operation, this score is generally scaled with different alternatives and each scaling option yields a new GAS model (Creal et al., 2011). Combination of GAS and state-space models enables the researcher to utilize all available information, to fill in missing values via Kalman filtering and eventually to model conditional correlations in high frequency set-up as shown by Buccheri et al. (2020). Authors uncover rising intraday average correlation during the day and a visible decline just before the closing bell in New York Stock Exchange.

In addition to inter-asset correlations in a market, different exchanges can have some degree of co-movement and trends in one market can visibly shape price formations of others. There is solid consensus in the literature on spillover effects. This is of no surprise with highly intertwined financial environment, multinational investor base and superfast information flow. Wojtowicz (2016) shows how different stock exchanges are correlated and how this interdependence evolves over different days of a week. By combining VAR and DCC-GARCH models, author finds Vienna and Warsaw stock exchanges to have significant intraday correlation with Frankfurt stock exchange. Similarly, Gjika and Horvath (2013) document the linked movements of three central European countries (Czech Republic, Hungary and Poland) between 2001-2011 and touch upon the asymmetric nature of volatility and conditional correlations. Likewise, Chandra (2006) tries to uncover day-of-the-week effect in stock returns and conditional correlations among Asia-Pacific exchanges. He reports day-of-the-week effect in returns for many of the stock markets analyzed and in pairwise conditional correlations for some countries.

On various topics, markets experience differing behaviors on different days of a week; shortly called as day-of-the-week anomaly. Among many examples, Birru (2018) measures return levels of speculative and non-speculative strategies on different weekdays and concludes speculative stocks to earn relatively low on Mondays and high on Fridays. Findings are based on psychological mood of investors over varying days of a week; mood is down on Mondays and up on Fridays. Balaban, Ozgen and Karidis (2018) analyze asymmetric conditional volatility of stock returns and price formations at Borsa Istanbul on each session of a day and find alternating but significant results for different parts of a week.

CHAPTER 3

MODEL AND METHODOLOGY

State-space models due to Kalman (1960) is quite convenient in dealing with high frequency data and is used to uncover the latent values. However, its usage is not confined to finance and applied in academic studies of the fields ranging from rocket science and navigation technologies to medicine.

State-space models, dynamic linear models in other words, has two pillars: state equation and the observation equation. The former in a general sense determines the rules how the data is generated with autoregressive manner. On the other hand, data is not directly observed as pictured in the state equation and thus the latter represents a linear transformation of the state vector to incorporate the data errors. In the framework of this study, similar to Buccheri et al. (2020), state equation serves for unearthing the efficient non-observable log-prices whereas observation equation unites market micro-structure effects with those efficient prices to reach the observed ones. State-space model can generally be written as (state and observation equations respectively):

$$X_{t+1} = X_t + n_t \qquad n_t \sim (0, Q_t) \tag{1}$$

$$Y_t = X_t + e_t \qquad e_t \sim (0, H_t) \tag{2}$$

Here n_t and e_t are conditionally normal based on the information existent at period $t-1$ and e_t are uncorrelated over different times and independent of the state vector X_t. In this framework, Kalman filter recursions can be written as:

$$v_t = Y_t - L_t a_t \tag{3}$$

$$a_t = a_{t-1} + K_{t-1} v_{t-1} \tag{4}$$

$$K_{t-1} = P_{t-1} L'_{t-1} F_{t-1}^{-1} \tag{5}$$

$$F_t = L_t (P_t + H_t) L'_t \tag{6}$$

$$P_t = P_{t-1}(I_n - K_{t-1} L_{t-1})' + Q_t \tag{7}$$

where a_t and P_t are respectively the conditional means and covariances of X_t vector at time $t - 1$ and I_n is the identity matrix with n being the number of assets analyzed simultaneously. v_t simply stands for error in the estimate in each iteration and F_t is its corresponding covariance matrix. Following Buccheri et al. (2020), L_t is designed as a selection matrix to assign the corresponding values consistently to the accompanying values in matrix calculations. Its dimension is changing in every step depending on the number of observed prices. Hence, it becomes an identity matrix when there is no missing price. However, Shumway and Stoffer (2017) sets it as an identity matrix, preserves the dimension and handles the missing observations by zeroing the corresponding rows. See also Durbin and Koopman (2012) for missing data modifications. Shumway and Stoffer (2017) includes also plain proofs of Kalman filter derivations and interested readers are referred to that study and references therein. Q_t is symbolized for the covariance matrix of efficient log prices and it can be decomposed as

$$Q_t = D_t R_t D_t \tag{8}$$

where R_t is the time-varying correlation matrix and D_t is $n\ x\ n$ standard deviations matrix constructed easily from Q_t by taking the square roots of the diagonal elements. In the above modelling, H_t is assumed to be diagonal to preserve the parsimony.

The purpose is to dynamically model the covariance matrices and parameterize the correlation matrix. As in Buccheri et al. (2020), Creal et al. (2013) and Creal et al. (2011), the time-varying parameters are gathered all together in a vector as:

$$f_t = \begin{bmatrix} \log(diag[H_t]) \\ \log(diag[D_t^2]) \\ \emptyset_t \end{bmatrix} \tag{9}$$

where $\emptyset_t$ represents the time-varying elements in the correlation matrix, which are basically the Jacobi rotation angles of a unit norm vector in respective planes without jeopardizing the unit norm structure. The number of elements depends on the parametrization of R_t. There are different ways to parameterize R_t; Buccheri et al. (2020), Creal et al. (2011) and Rapisarda et al. (2007) uses hyper spherical coordinates and R_t is further depicted with Cholesky decomposition as

$$R_t = Z_t' Z_t \tag{10}$$

where Z_t is shown as the following matrix in which $c_{ij} = cos\theta_{ij}$ and $s_{ij} = sin\theta_{ij}$

$$Z_t = \begin{bmatrix} 1 & c_{12} & c_{13} & \cdots & c_{1n} \\ 0 & s_{12} & c_{23}s_{13} & \cdots & c_{2n}s_{1n} \\ 0 & 0 & s_{23}s_{13} & \cdots & c_{3n}s_{2n}s_{1n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \prod_{k=1}^{n-1} s_{kn} \end{bmatrix} \tag{11}$$

In this setting, each column is unit norm and is composed of the hyper spherical coordinates in n-dimensional space. Hence, given the number of assets being analyzed is n, there will be $\frac{n(n-1)}{2}$ different asset pairs, angles, and correlations. Together with the ones in H_t and D_t, time-varying parameters sum up to $2n + \frac{n(n-1)}{2}$ for each time period. When the number of assets studied at once is 5 for instance, there will be twenty parameters we will be after to forecast. On the other hand, there are some alternative parameterizations for R_t, one of which is DECO due to Engle and Kelly (2012).

Here, formulating the evolution of time-varying parameters which are all piled in vector f_t, is one of the crucial tasks during the model construction. Buccheri et al. (2020), Delle Monache et al. (2016), Creal et al. (2013) and Creal et al. (2011) set updating mechanism for f_t as a GAS model:

$$f_{t+1} = c + As_t + Bf_t \tag{12}$$

where s_t is the information from previous period and can be magnified by taking the product of the score and Fisher information matrix:

$$\nabla_t = \left[\frac{\partial \log p(Y_{t|f_t}, \mathcal{F}_{t-1}, \Phi)}{\partial f_t'}\right]' \tag{13}$$

$$\zeta_{t|t-1} = E[\nabla_t \nabla_t'] \tag{14}$$

$$s_t = (\zeta_{t|t-1})^{-1} \nabla_t \tag{15}$$

where $\mathcal{F}_{t-1}$ represents the information or prior knowledge of observations for conditionality. Shortly, Fisher information matrix is the scaling factor of the score. Following Buccheri et al., (2020), c, A and B are assumed to be static in the GAS filter and can be predicted via maximum likelihood estimation by preserving the non-stationary dynamics of the time-varying parameters.

In the model, some parameter restrictions are needed to ensure the non-negativity of innovation variances and to set the boundary for time-varying angles. The former is achieved via a suitable link function. While taking the derivative of log-likelihood function with respect to time-varying parameters, the vector in question will be $\tilde{f}_t$ instead of f_t as discussed in Buccheri et al. (2020) and Creal et al. (2013).

$$\tilde{f}_t = \begin{bmatrix} diag[H_t] \\ diag[D_t^2] \\ \emptyset_t \end{bmatrix} \tag{16}$$

Here the connection between $\tilde{f}_t$ and f_t will be set up via the following link function $W(f_t)$ and the inverse of it will simply yield f_t. Since the conditional derivations move upon $\tilde{f}_t$ vector, the accompanied Jacobian (J_W) must also be injected to the model. That as a result implies the application of chain rule to the score (∇_t) and Fisher information matrix ($\zeta_{t|t-1}$) calculations and respective formulations are also available in the appendix to Buccheri et al. (2020).

$$\tilde{f}_t = W(f_t) = \begin{bmatrix} exp\, f_t^1 \\ \vdots \\ exp\, f_t^{2*n} \\ \emptyset_t \end{bmatrix} \tag{17}$$

$$J_W = \left(\frac{\partial \tilde{f}_t}{\partial f_t'}\right) = \begin{bmatrix} H_t & 0_{nxn} & 0_{nxq} \\ 0_{nxn} & D_t^2 & 0_{nxq} \\ 0_{qxn} & 0_{qxn} & I_q \end{bmatrix} \quad (18)$$

$$\nabla_t = J_W \widetilde{\nabla}_t \; and \; \zeta_{t|t-1} = J_W \tilde{\zeta}_{t|t-1} J_W \quad (19)$$

Prediction error decomposition -which is originally due to Schweppe (1965)- is used as the likelihood function in state-space models' framework. Conditionally, log-likelihood function turns out to be as following in prediction error decomposition form:

$$\log p(Y_{t|f_t}, \mathcal{F}_{t-1}, \Phi) = -0.5\log 2\pi - 0.5T log\sigma^2 - 0.5\sum_t log|F_t| + v_t' F_t^{-1} v_t \quad (20)$$

At every stage, Kalman filtering and time-varying parameter estimation should be run concurrently. Buccheri et al. (2020) and Delle Monache et al. (2016) clearly formulates the ingredients $\widetilde{\nabla}_t$ and Fisher information matrix as:

$$\widetilde{\nabla}_t = -0.5\left[\ddot{F}_t'\left(I_{n_t} \otimes F_t^{-1}\right) vec\left(I_{n_t} - v_t v_t' F_t^{-1}\right) + 2\ddot{v}_t' F_t^{-1} v_t\right] \quad (21)$$

$$\tilde{\zeta}_{t|t-1} = 0.5[\ddot{F}_t'(F_t^{-1} \otimes F_t^{-1})\ddot{F}_t + 2\ddot{v}_t' F_t^{-1} \ddot{v}_t \quad (22)$$

where one can compute $\ddot{v}_t$ and $\ddot{F}_t$ by deriving v_t and F_t conditionally with respect to vector $\tilde{f}_t'$.

Accompanied derivation results are presented in Buccheri et al. (2020) and Delle Monache et al. (2016) where sequential recursions are listed additionally in the latter. Derivation of a matrix with respect to another matrix (or a vector) can be seen and practiced in respective chapters of Abadir and Magnus (2005). Following Buccheri et al. (2020) and Delle Monache et al. (2016),

$$\ddot{v}_t = -L_t \ddot{a}_t \tag{23}$$

$$\ddot{F}_t = (L_t \otimes L_t)\big(\ddot{P}_t + \ddot{H}_t\big) \tag{24}$$

$$\ddot{a}_{t+1} = \ddot{a}_t + (v_t' \otimes I_n)\ddot{K}_t + K_t \ddot{v}_t \tag{25}$$

$$\ddot{P}_{t+1} = \ddot{P}_t - (K_t L_t \otimes I_n)\ddot{P}_t - (I_n \otimes P_t L_t')C_{nn_t}\ddot{K}_t + \ddot{Q}_t \tag{26}$$

$$\ddot{K}_t = (F_t^{-1} L_t \otimes I_n)\ddot{P}_t - (F_t^{-1} \otimes K_t)\ddot{F}_t \tag{27}$$

$$\ddot{Q}_t = [(D_t R_t \otimes I_n) + (I_n \otimes D_t R_t)]\ddot{D}_t + (D_t \otimes D_t)\ddot{R}_t \tag{28}$$

where $\otimes$ represents the Kronecker product and $\ddot{H}_t$, $\ddot{D}_t$ and $\ddot{R}_t$ are calculated as shown below. C_{nn_t} stands for commutation matrix, a member of permutation matrices family. Before proceeding, it is helpful to note that derivative of an $a\ x\ b$ matrix with respect to another matrix of $c\ x\ d$ will be of dimensions $ab\ x\ cd$. In that regard, $\ddot{H}_t$, $\ddot{D}_t$ and $\ddot{R}_t$ will all be of $n^2\ x\ k$ dimensions in the following structure:

$$\ddot{H}_t = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 & 0 & \cdots & \cdots & \cdots & \cdots & 0 \\ 0 & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 1 & 0 & \cdots & 0 & 0 & \cdots & \cdots & \cdots & \cdots & 0 \\ \vdots & 0 & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 1 & 0 & \cdots & \cdots & \cdots & \cdots & 0 \end{bmatrix} \tag{29}$$

$$
\ddot{D}_t = 0.5 \begin{bmatrix} 0 & \cdots & 0 & \frac{1}{D_{t,11}} & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & 0 & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \cdots & 0 & 0 & \cdots & \frac{1}{D_{t,22}} & 0 & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & 0 & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \cdots & 0 & 0 & \cdots & 0 & 0 & \cdots & \frac{1}{D_{t,nn}} & 0 & \cdots & 0 \end{bmatrix} \quad (30)
$$

$$
\ddot{R}_t = [(Z_t' \otimes I_n) C_{nn} + (I_n \otimes Z_t')] \ddot{Z}_t \quad (31)
$$

When deriving Z_t with respect to vector $\tilde{f}_t$, derivations for the first $2n$ elements of the vector $\tilde{f}_t$ will be 0 where the derivations with respect to the remaining $\frac{n(n-1)}{2}$ items, which are mainly the hyperspherical angles, will be of the following magnitudes as shown in Creal et al. (2011) and Buccheri et al. (2020):

$$
\frac{\partial Z_{ij}}{\partial \emptyset_{lm}} = \begin{cases} 0, & i > j, \quad j \neq m, \quad l \geq m, \quad l > i \\ -Z_{ij} \tan \emptyset_{ij}, & i < j, \quad l = i \\ \frac{Z_{ij}}{\tan \emptyset_{lj}}, & otherwise \end{cases} \quad (32)
$$

Model is quite flexible, and it heralds new avenues in high frequency set-up. When the number of analyzed stocks increases, all that must be done is to rearrange the data frame accordingly at the cost of larger matrix dimensions and therewith increasing calculation time. Fortunately, available computer programs can effortlessly undertake this burden and create room for more comprehensive analysis.

It is quite rare for all stocks to be traded at the same moment, hence have simultaneous observations at a given time stamp. In other words, there will be missing observations for some stocks while others will have trades at a given time frame, which is each second in most studies including this one. Even though the model encompasses missing data modifications, relative variances rise too when there are more missing data. In order as much to avoid that as possible, stocks with highest observation numbers are selected for the study. This shortcoming is also valid when the researcher selects mostly traded stocks but desires to uncover conditional correlations at sub-second intervals. To put it differently, a research design with less frequently traded stocks at one-second interval is prone to akin drawbacks with a design aiming sub-second intervals with most frequently traded shares. That implicitly means, this model will even be functioning properly in a trading environment in which there are quite many deals at sub-second levels and this is highly probable in the near future due to the soaring algorithmic trading activity.

CHAPTER 4

DATA AND TRADING RULES

4.1 Data

Data consists of tick-by-tick trades from the third quarter of 2018 for the ten most liquid stocks traded at Borsa Istanbul Equity Market. During the period that data is collected, there was a half-day and a day in which the Exchange was partially closed due to glitch in data dissemination channel. Hence, those days are not included in the analysis and rest of the days are treated in isolation. There were 25203 data points for one single day including the opening session price which is used as the initial price for each day's iteration. In the case where more than one price quotations coincide on the same second, median is used as suggested in Barndorff-Nielsen et al. (2009). This multivariate model is run with ten stocks that have the highest number of average observations for the period.

Index constituents are updated quarterly at Borsa Istanbul. Even though the analyzed stocks are from XU030 index in the third quarter of 2018, this condition is additionally checked if it was also the case in second and fourth quarters of the same year. This is crucial in the sense that stocks' betas converge to that of the index they are added to. Vijh (1994) shows that non-S&P 500 stocks' betas increase after their inclusion to S&P 500. Barberis et al. (2005) similarly report this co-movement when stocks are put into certain index and touch upon the factors of "friction-based" convergence. Even though days are analyzed separately in the thesis, requirement of index membership before and after the third quarter of 2018 eliminates these latent drivers in correlation structure.

Calculations to draw intraday dynamic correlation figures are performed in two steps:

I. Arithmetic mean of the upper triangular matrix of R_t for each time stamp in a given day is stored.

II. Numbers of a given time stamp for all days are then averaged.

Kalman filter fills in the missing data points by exploiting the information and correlation dynamics embedded in the observed prices. This is called as signal extraction in the relevant literature like Shumway and Stoffer (2017) and Corsi et al. (2015). State equation rests on randomly walking efficient prices. This implies that the next period's price will conditionally be equal to that of the current period. A profound look into the observations strongly supports this assumption. In XU030, around 60% of the quoted prices are equal to its preceding values in majority of the stocks selected (Figure 1). Similarly, 58.5% of Boeing stock transactions on December 1, 2008 had no price change when the consecutive trades are considered (Tsay, 2010, p. 243).

Respective software codes are developed with Python programing language on Jupyter Notebook in the Anaconda Environment.

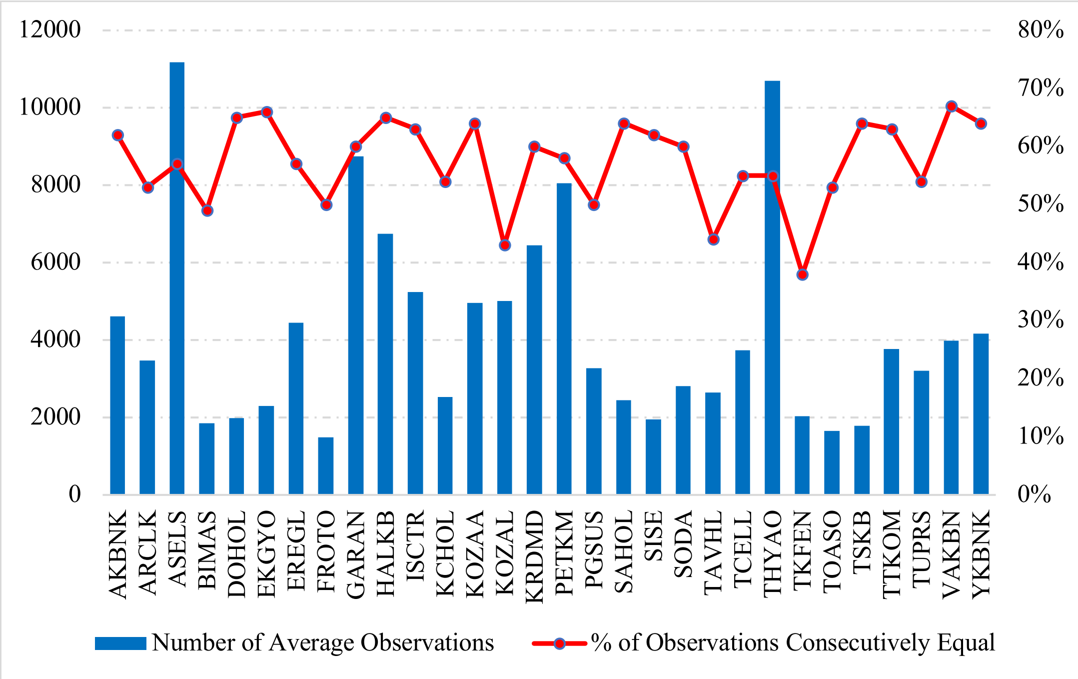

Figure 1. Number of Daily Average Observations and Percentage of Consecutively Equal Prices

Source: Borsa Istanbul, 2018 third quarter

A snapshot of the log prices for a 10-second period is tabulated in Table 1. Empirical analysis is conducted with more frequently traded stocks and Table 2 reports pertinent observation statistics.

Table 1. A Snapshot of Observations (log-prices) for 10 Seconds in a Random Day

Time	ASELS	THYAO	GARAN	PETKM	HALKB	KRDMD	ISCTR	KOZAL	AKBNK	YKBNK
11:41:39	3.26576	2.66445	2.14242	Nan	Nan	Nan	1.74397	3.77368	Nan	Nan
11:41:40	3.26652	2.66445	2.14242	Nan	2.0149	Nan	Nan	Nan	Nan	Nan
11:41:41	Nan	2.66514	2.14242	1.50851	Nan	Nan	Nan	Nan	Nan	Nan
11:41:42	Nan	Nan	2.14242	Nan	Nan	Nan	Nan	3.77299	Nan	0.90422
11:41:43	Nan	2.66479	2.14242	Nan	Nan	Nan	Nan	3.77345	Nan	Nan
11:41:44	Nan	2.66445	Nan	1.51072	2.0149	1.56653	Nan	Nan	Nan	Nan
11:41:45	3.26652	2.66445	Nan	1.50851	Nan	1.56653	Nan	Nan	2.02419	0.90422
11:41:46	3.26652	Nan	2.14242	1.51072	Nan	Nan	Nan	3.77368	Nan	0.90422
11:41:47	3.26652	2.66445	Nan	Nan	Nan	1.56653	Nan	Nan	2.02419	Nan
11:41:48	3.26652	2.66445	Nan	Nan	2.0149	Nan	Nan	Nan	Nan	0.90422

Table 2. Observation Statistics of the Analyzed Stocks

Ticker Symbol	Company	Consecutively Equal Observations	Number of Average Observations	Probability of Missing Value	Average Duration (Seconds)
ASELS	Aselsan	57%	11,174	0.56	2.3
THYAO	Turkish Airlines	55%	10,699	0.58	2.4
GARAN	Garanti Bank	60%	8,749	0.65	2.9
PETKM	Petkim Petrochemistry	58%	8,050	0.68	3.1
HALKB	Halkbank	65%	6,745	0.73	3.7
KRDMD	Kardemir (Group D)	60%	6,444	0.74	3.9
ISCTR	Is Bank (Group C)	63%	5,247	0.79	4.8
KOZAL	Koza Gold	43%	5,015	0.8	5
AKBNK	Akbank	62%	4,613	0.82	5.5
YKBNK	Yapikredi Bank	64%	4,175	0.83	6

4.2 Trading rules

As is stated, opening session prices are used as the beginning prices for each day in Kalman filtering. Opening session is designed as a single-price auction in which all the orders are collected for fifteen minutes and the price that enables the highest trading volume according to the methodology presented in respective directives is announced as the opening session price. In other words, all the awaiting eligible orders are matched with the price that meets the criteria specified in the relevant regulation.

Continuous auction starts at 10:00 and there is one hour of break between 13:00 and 14:00. Hence there exists two sessions in a typical day for the analyzed period (According to the current rules, this session break is abolished). In spite of the presence of a closing session which is held after 18:00, last price for a day is set to the one quoted at 18:00 for the sake of brevity.

When an order is matched with a counter order, a trade contract is created with the accompanying time stamp. Although there are occasionally many trades which coincide with a given time stamp, the median is set as the sole price for that second. Actually, in the case when lots of deals exist on sub-second levels, majority of them are seen to be of 1-unit quantity following each other with millisecond time differences between successive trades. No doubt, this picture is drawn by the algorithms.

Stocks on the Exchange may have different clearing and settlement rules depending on which group of market they are listed in. If there is no special measure taken for some reason, XU030 index stocks are traded with net settlement method in which buy and sell trades are netted separately for client and house orders. In contrast to gross settlement method in which the netting mechanism is switched off, liquidity is higher in net-settled stocks.

CHAPTER 5

EMPIRICAL FINDINGS

5.1 Intraday conditional correlation patterns

At Borsa Istanbul Equity Market, average correlation starts rising after the ring bells, wanders around certain levels and gradually rises after 16:30 with US market openings (Figure 2). The rise in the last part of the day is more overt for some weekdays and periods (Figure 4). Driving forces of daily conditional pattern can be split into two classes: firm-specific impacts and market factors (Allez and Bouchaud, 2011; Buccheri et al., 2020; Tilak et al., 2013). Drastic surge after the trading kicks of leans on idiosyncratic news and sector-wise events that are piled up after previous day's market closure. Afterwards, market factor becomes dominant in governing average conditional correlation figures.

Day-of-the-week decomposition divulges no considerable discrepancy in idiosyncratic determinants among weekdays whereas market dynamics shapes intraday conditional correlation differently on different days. It starts rising around US market openings on Mondays, Tuesdays and Fridays, with Mondays having the steepest increase. This seems reasonable when we think of accumulated information over the weekend.

The study covers three-month time frame that also includes the brief period in August 2018, when markets were hit by turmoil due to currency depreciation. In the period between August 8-August 15, conditional correlation numbers climbed further above the averages because of the market turmoil (Figure 3). Visibly, US market openings strongly affect stocks' co-movement during aforementioned market conditions. Straight lines on the figures indicate midday session breaks.

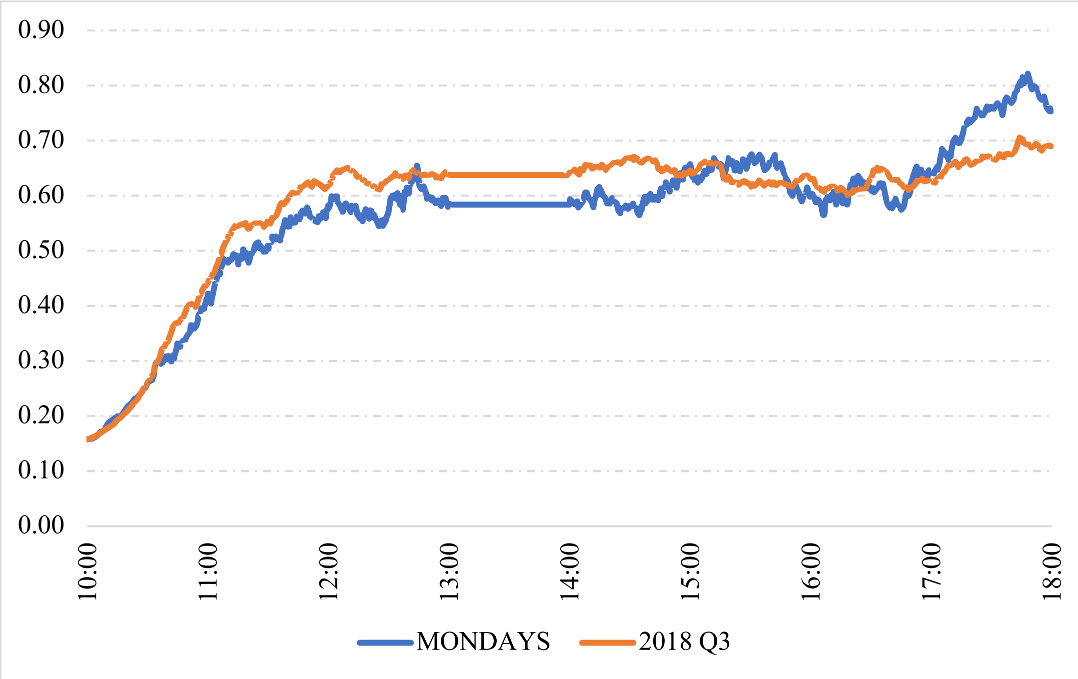

Figure 2. Average conditional correlations across 45 pairs of all 10 stocks on Mondays and over the entire study period of 2018 Q3

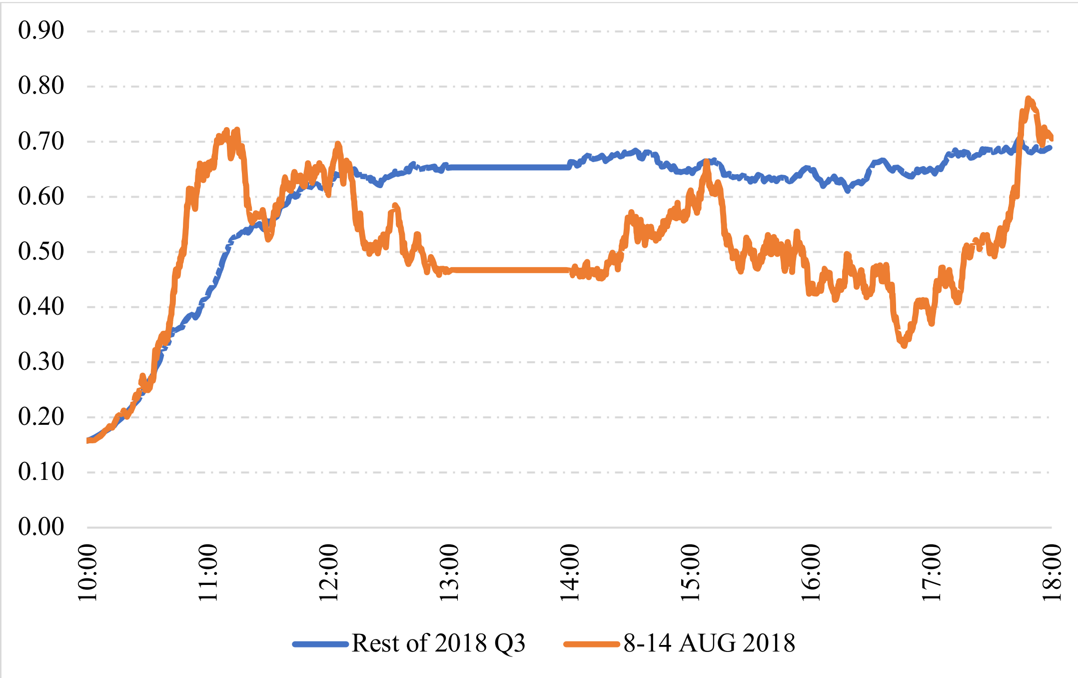

Figure 3. Average conditional correlations across 45 pairs of all 10 stocks unveiling how disorderly market conditions affect market-wide correlation levels

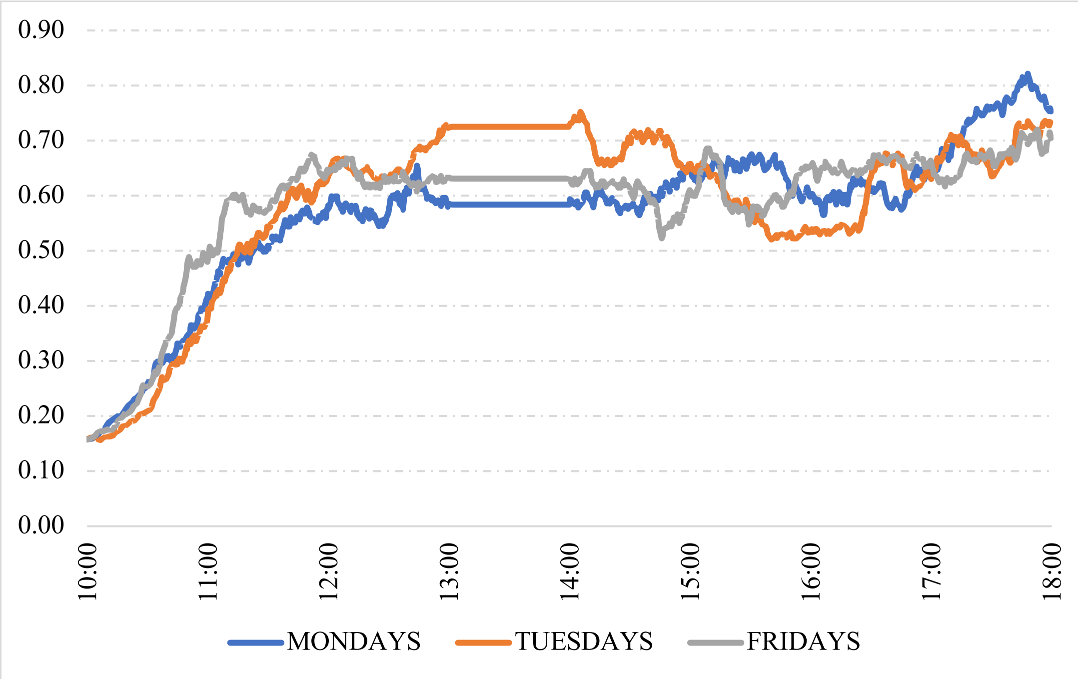

Figure 4. Average conditional correlations across 45 pairs of all 10 stocks allowing visual inspection for day-of-the-week distinction on Mondays, Tuesdays and Fridays

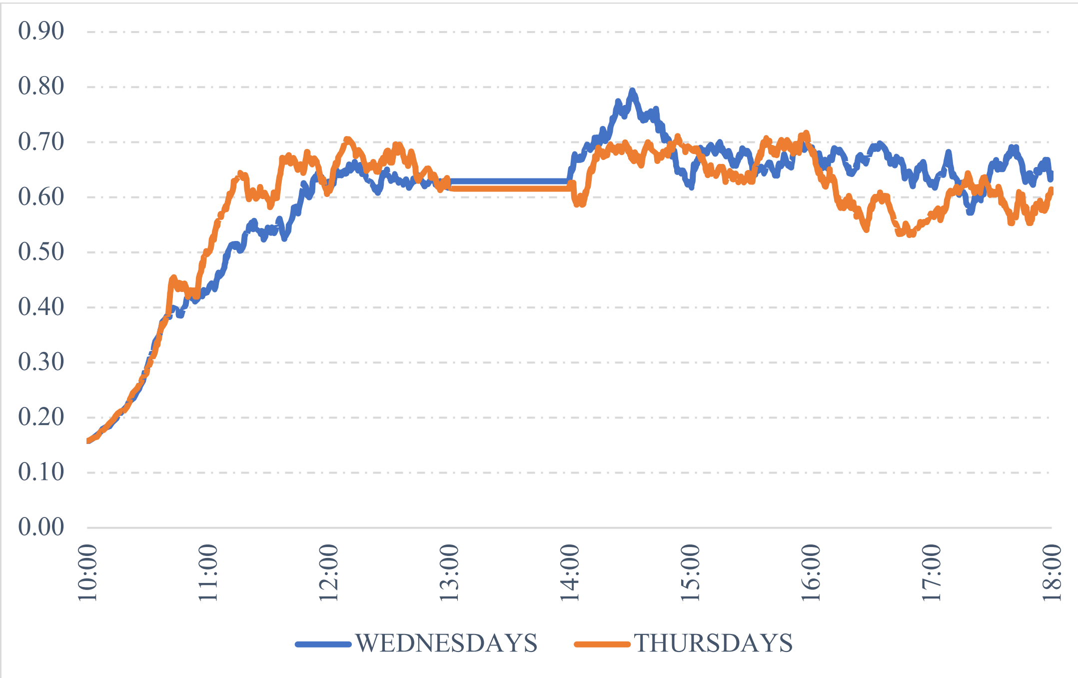

Figure 5. Average conditional correlations across 45 pairs of all 10 stocks allowing visual inspection for day-of-the-week distinction on Wednesdays and Thursdays

Deeper analysis into the numbers was accomplished by grouping stock pairs according to the sector. 5 of the ten stocks studied belong to banking sector and remaining companies operate in various fields. Off-diagonal elements of the correlation matrix are comprised of forty-five different pairs; of which ten pairs completely belong to banking industry, ten pairs to non-banking group and rest of the pairs include one banking stock and are gathered under banking/non-banking class.

From Figure 6 to Figure 17, intra-group trends are shown respectively in Banking, Non-Banking and Banking/Non-Banking fragmentation. Figure 18 to Figure 21 depicts inter-group comparison on different days and the whole analysis period.

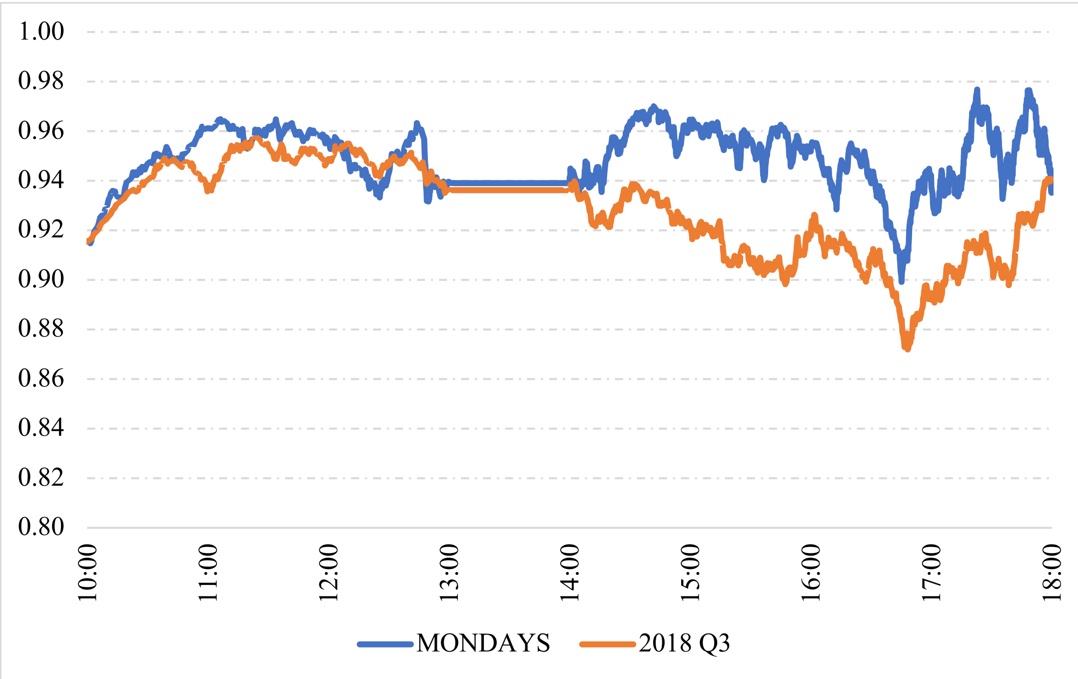

Figure 6. Average conditional correlations across 10 pairs of 5 banking stocks on Mondays and on the whole period

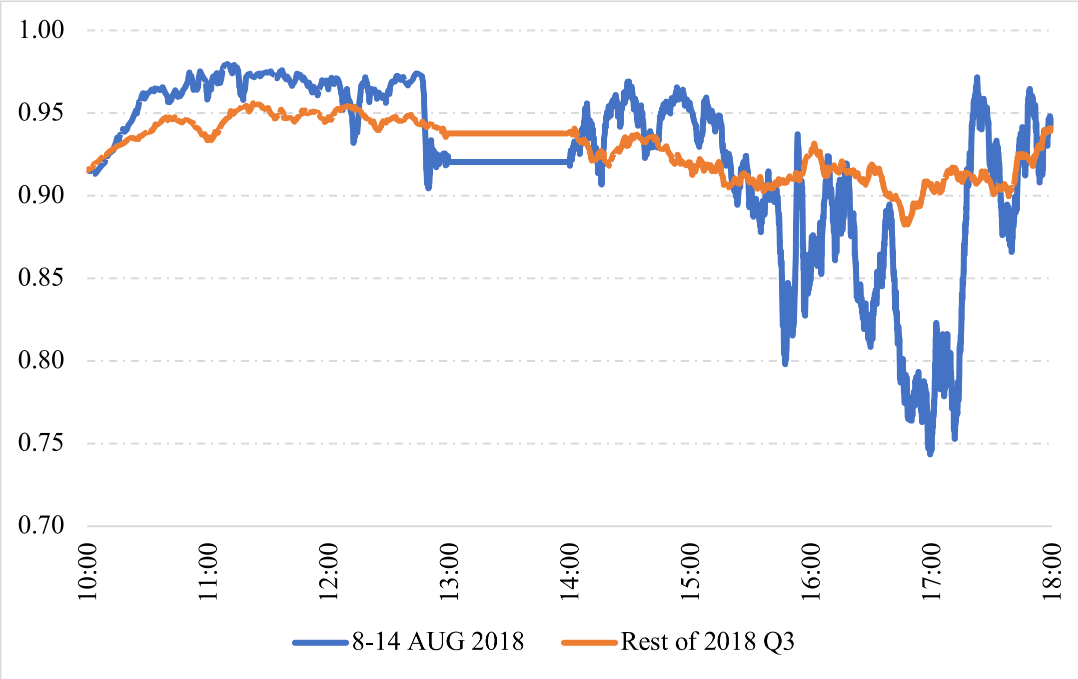

Figure 7. Average conditional correlations across 10 pairs of 5 banking stocks unveiling how disorderly market conditions affect correlation numbers

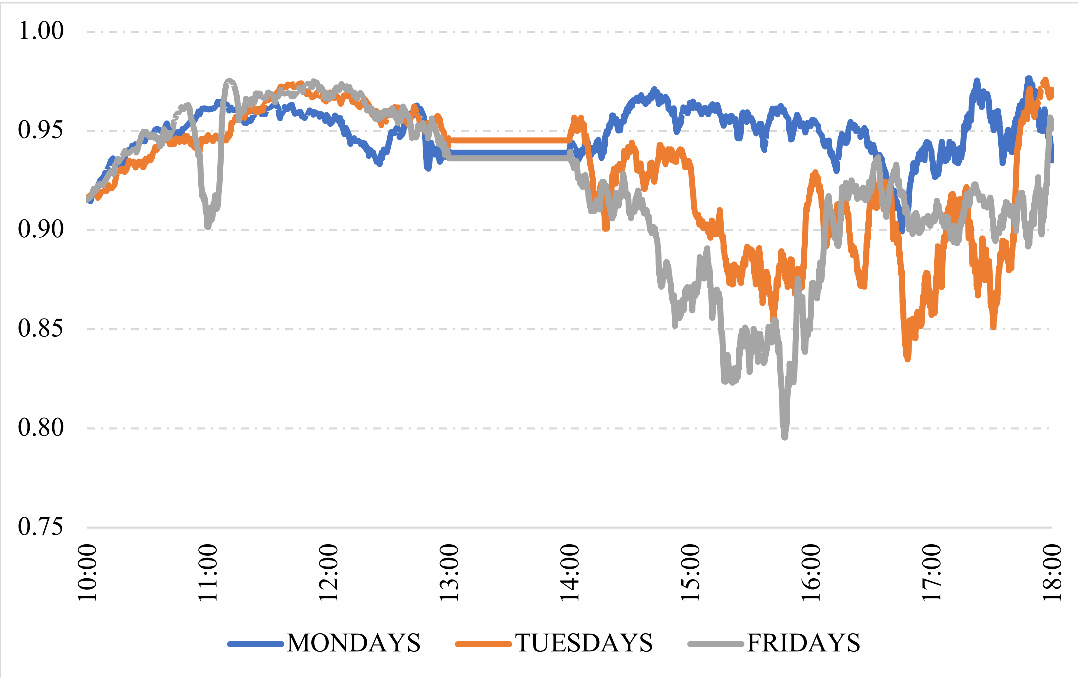

Figure 8. Average conditional correlations across 10 pairs of 5 banking stocks allowing visual inspection for day-of-the-week distinction on Mondays, Tuesdays and Fridays

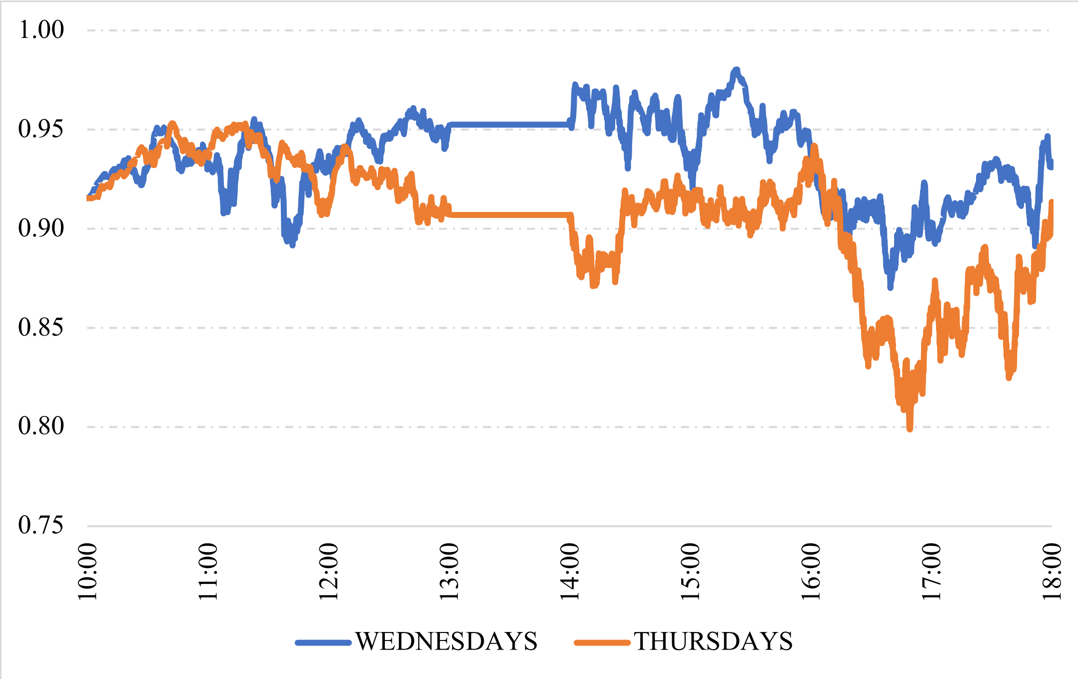

Figure 9. Average conditional correlations across 10 pairs of 5 banking stocks allowing visual inspection for day-of-the-week distinction on Wednesdays and Thursdays

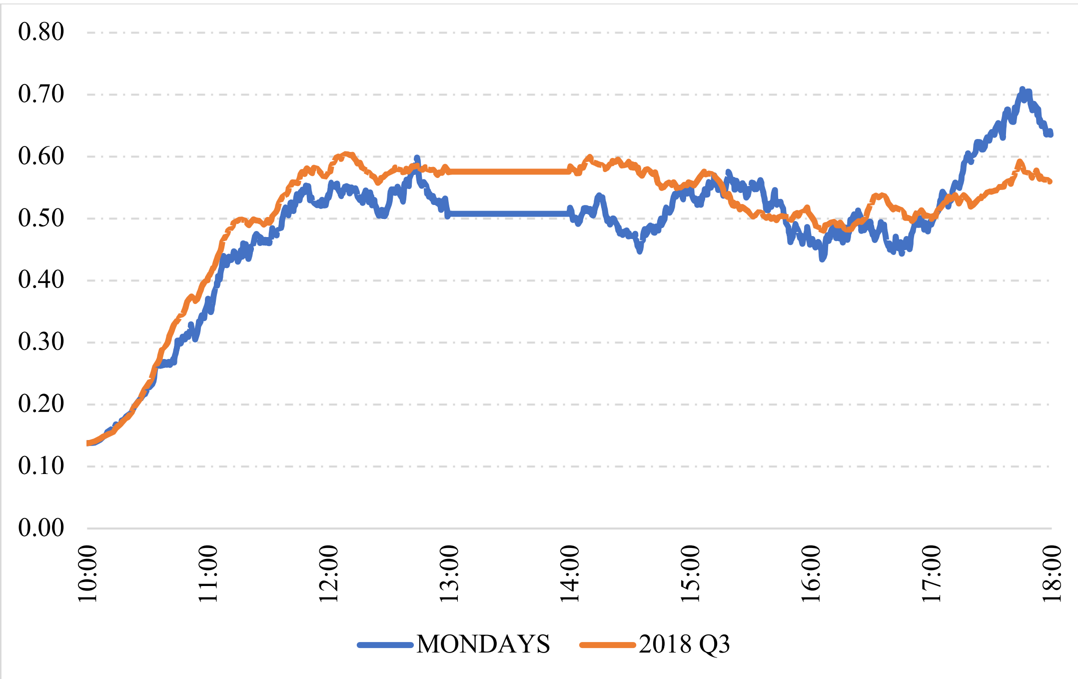

Figure 10. Average conditional correlations across 10 pairs of 5 non-banking stocks on Mondays and on the whole period

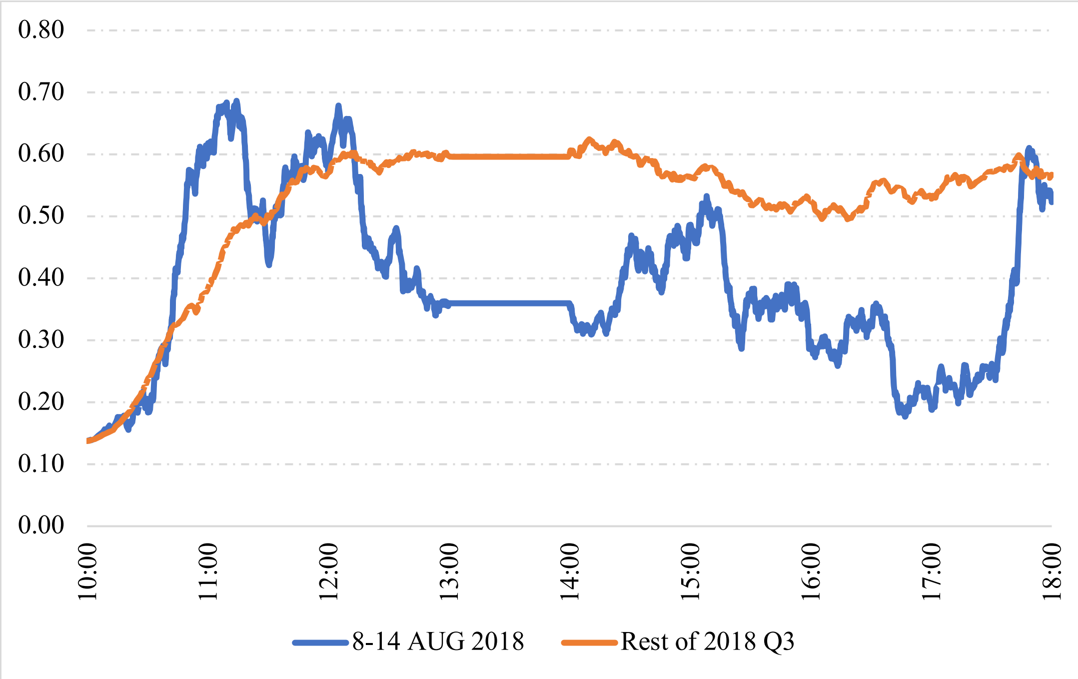

Figure 11. Average conditional correlations across 10 pairs of 5 non-banking stocks unveiling how disorderly market conditions affect correlation numbers

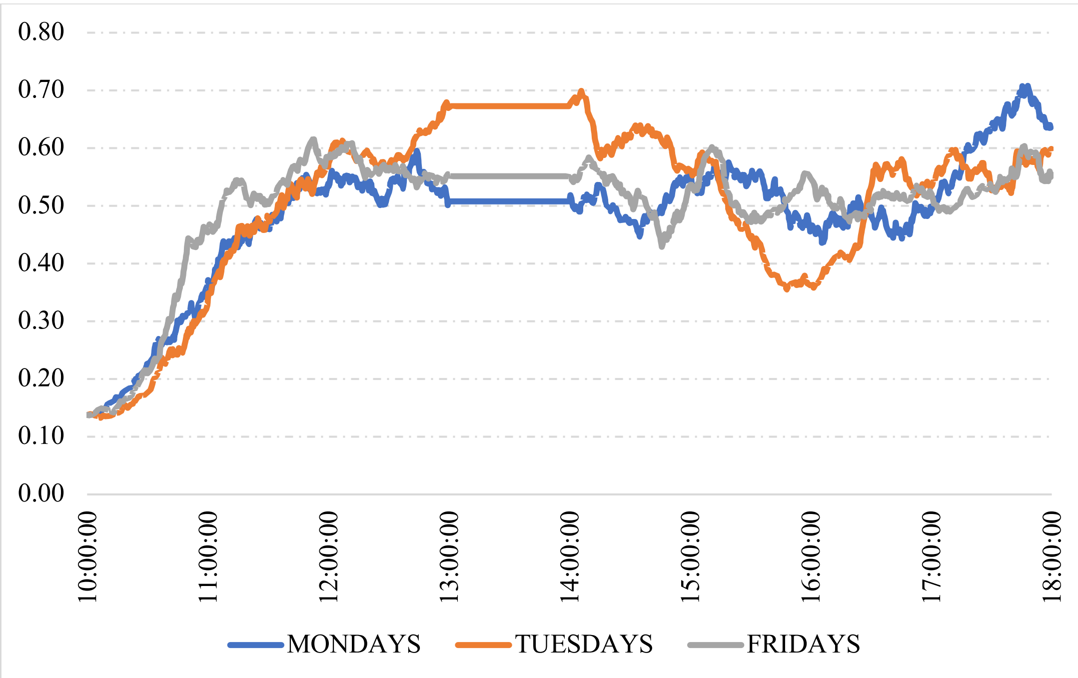

Figure 12. Average conditional correlations across 10 pairs of 5 non-banking stocks allowing visual inspection for day-of-the-week distinction on Mondays, Tuesdays and Fridays

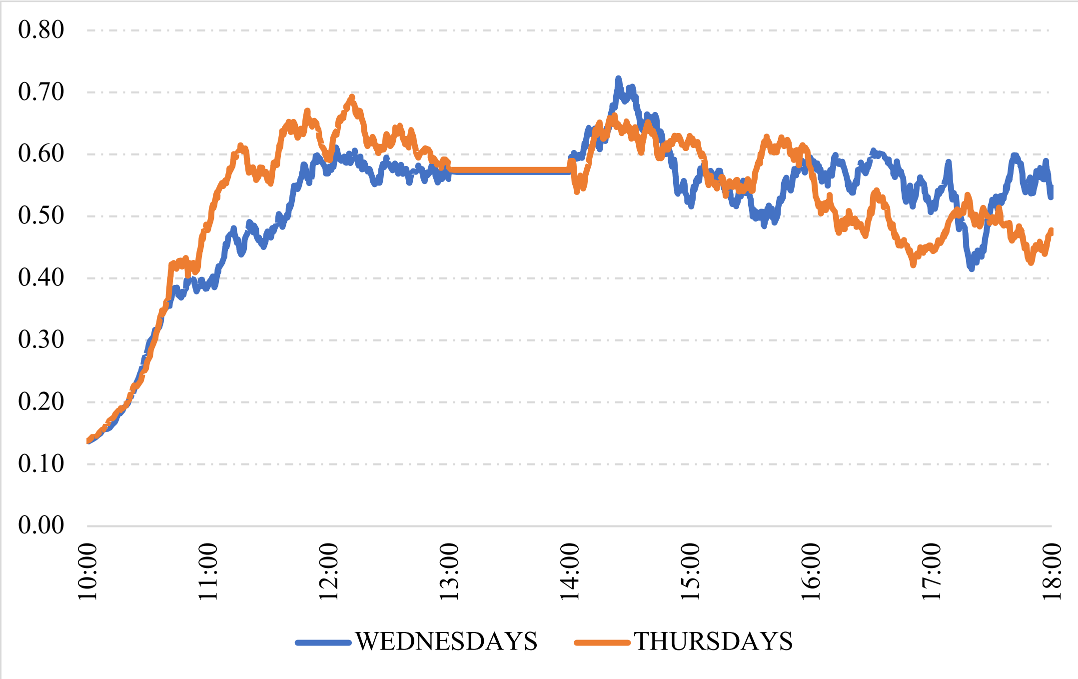

Figure 13. Average conditional correlations across 10 pairs of 5 non-banking stocks allowing visual inspection for day-of-the-week distinction on Wednesdays and Thursdays

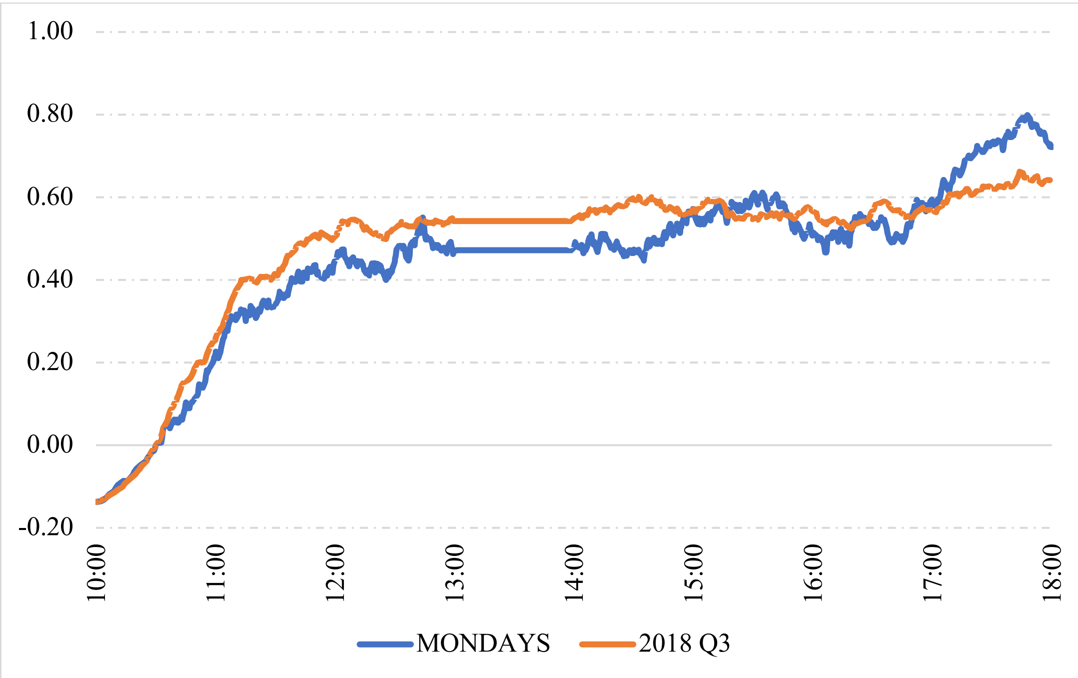

Figure 14. Average conditional correlations across 25 pairs of 5 banking and 5 non-banking stocks on Mondays and on the whole period

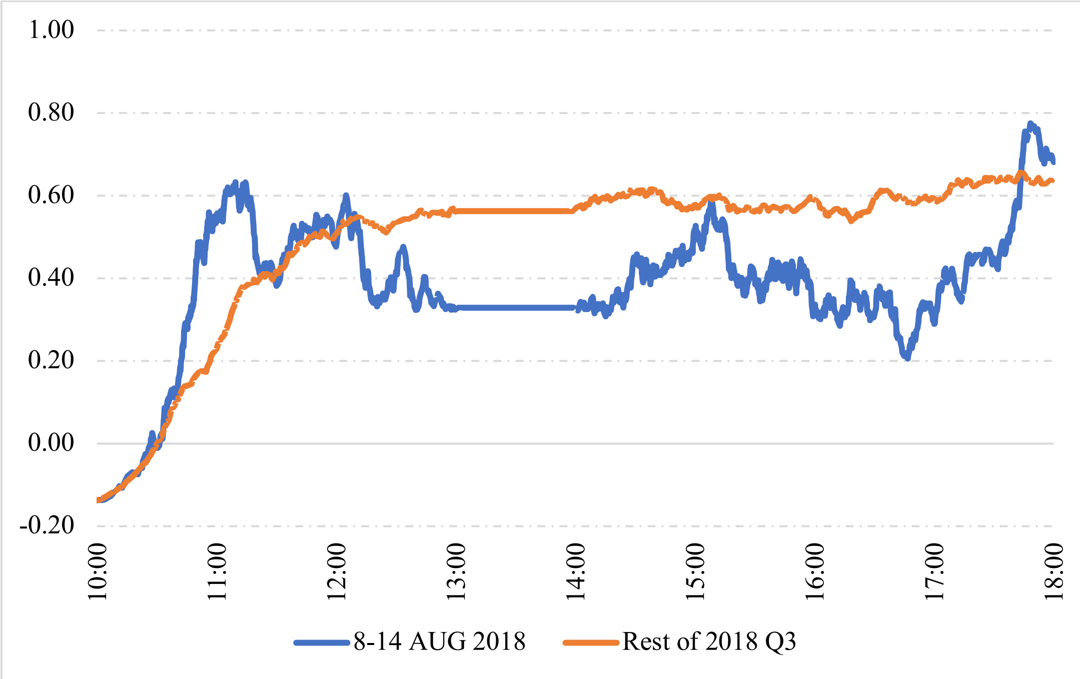

Figure 15. Average conditional correlations across 25 pairs of 5 banking and 5 non-banking stocks unveiling how disorderly market conditions affect correlation numbers

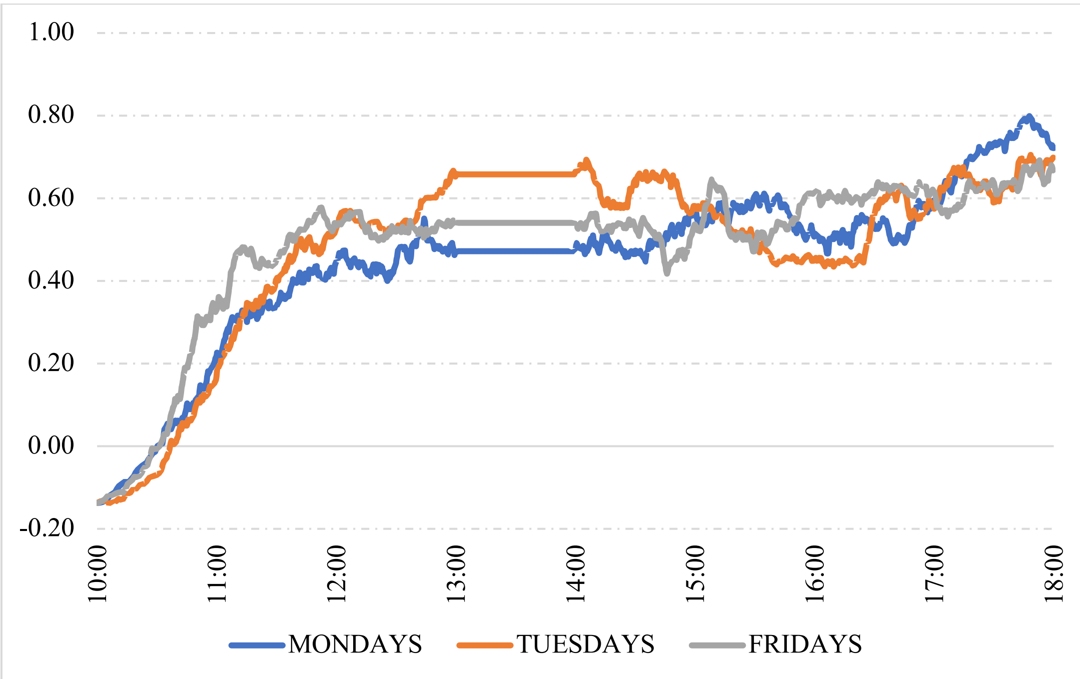

Figure 16. Average conditional correlations across 25 pairs of 5 banking and 5 non-banking stocks allowing visual inspection for day-of-the-week distinction on Mondays, Tuesdays and Fridays

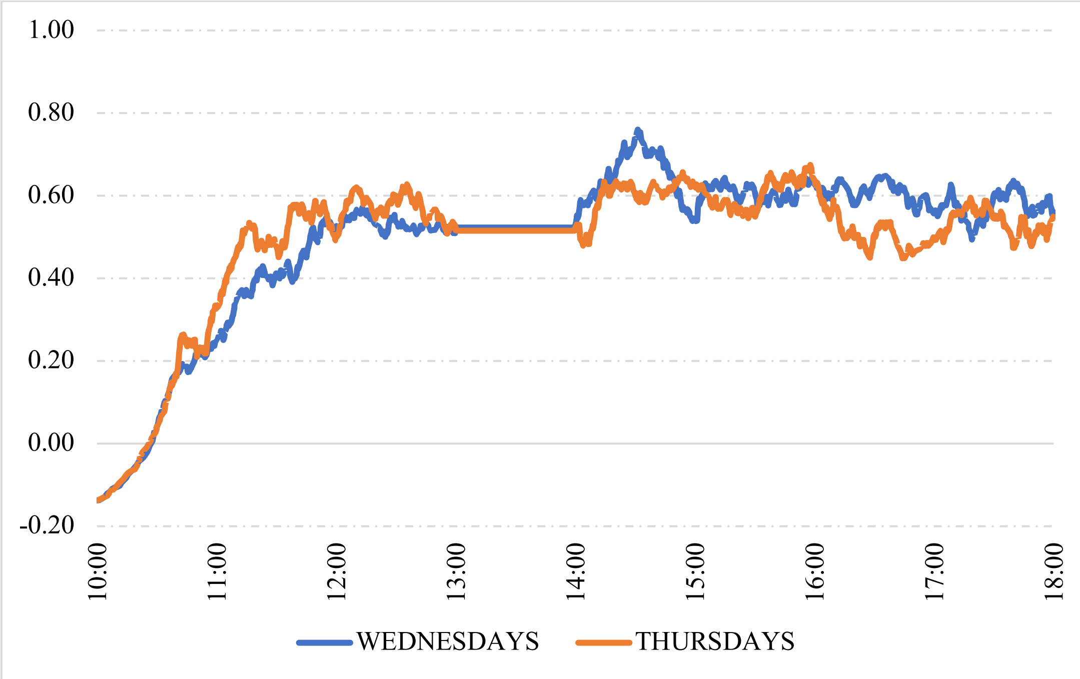

Figure 17. Average conditional correlations across 25 pairs of 5 banking and 5 non-banking stocks allowing visual inspection for day-of-the-week distinction on Wednesdays and Thursdays

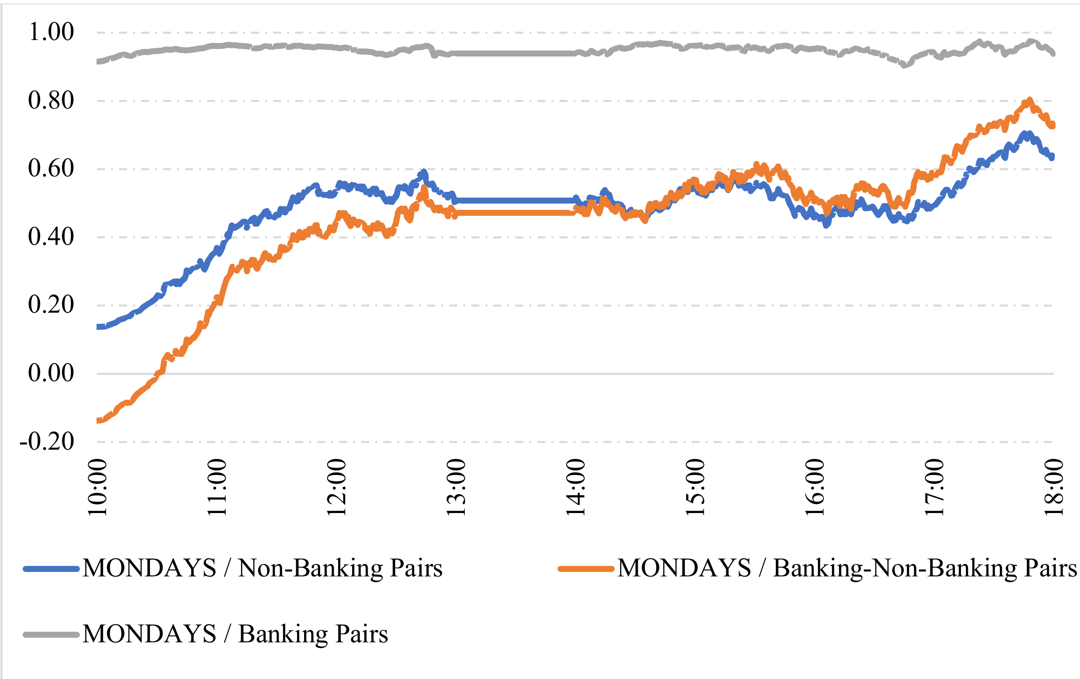

Figure 18. Comparison of average conditional correlations across different stock-pair groups for Mondays

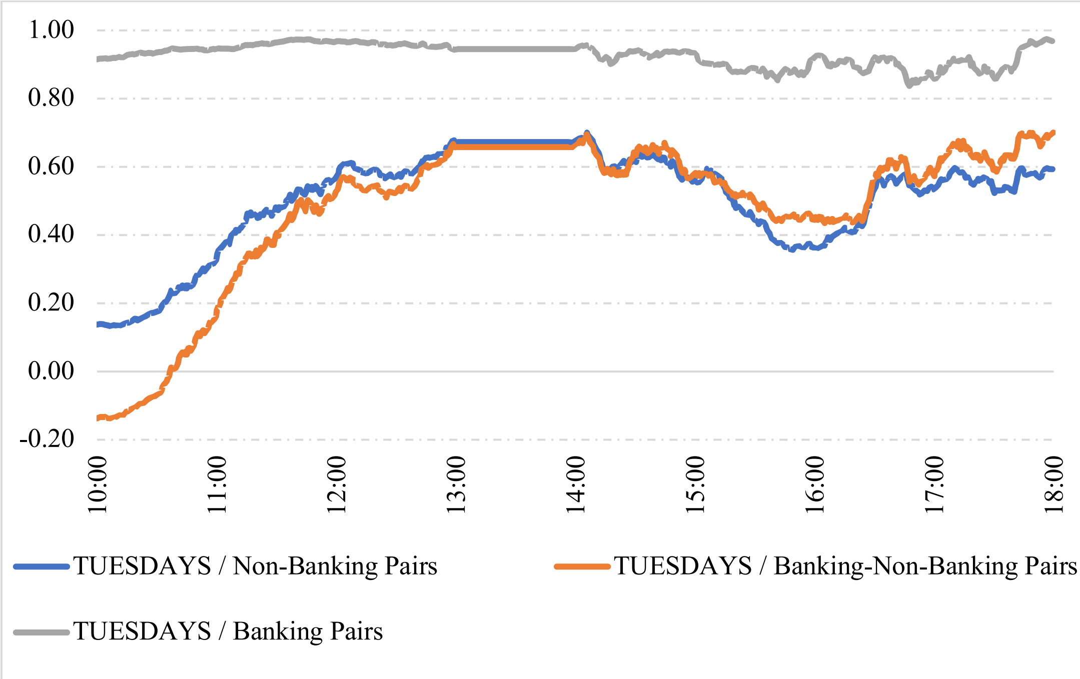

Figure 19. Comparison of average conditional correlations across different stock-pair groups for Tuesdays

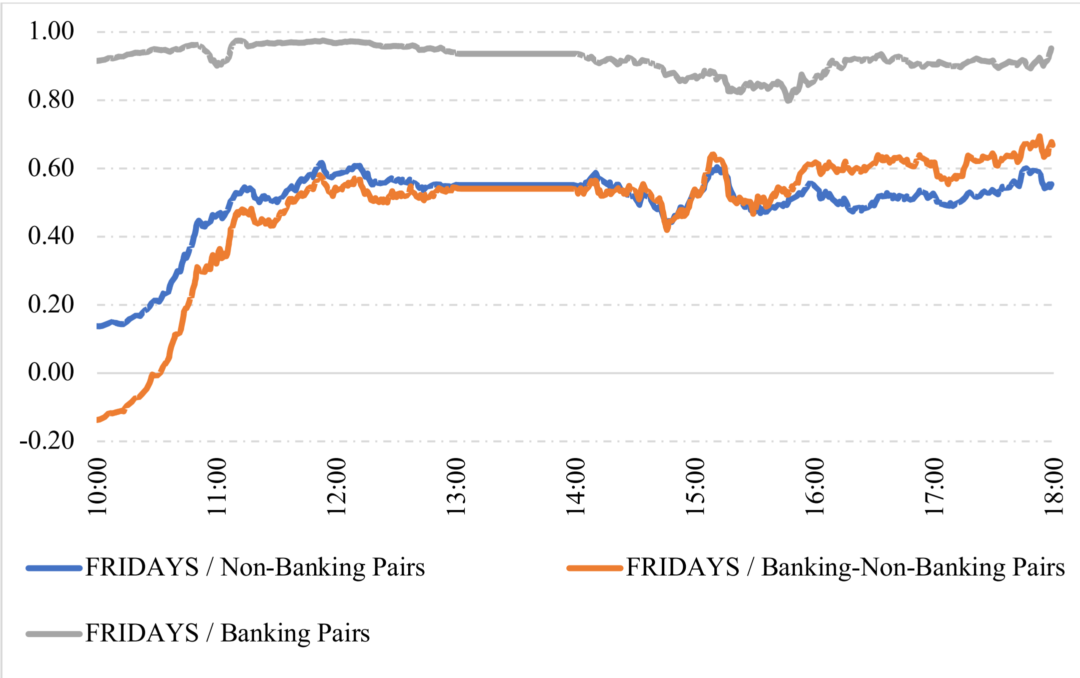

Figure 20. Comparison of average conditional correlations across different stock-pair groups for Fridays

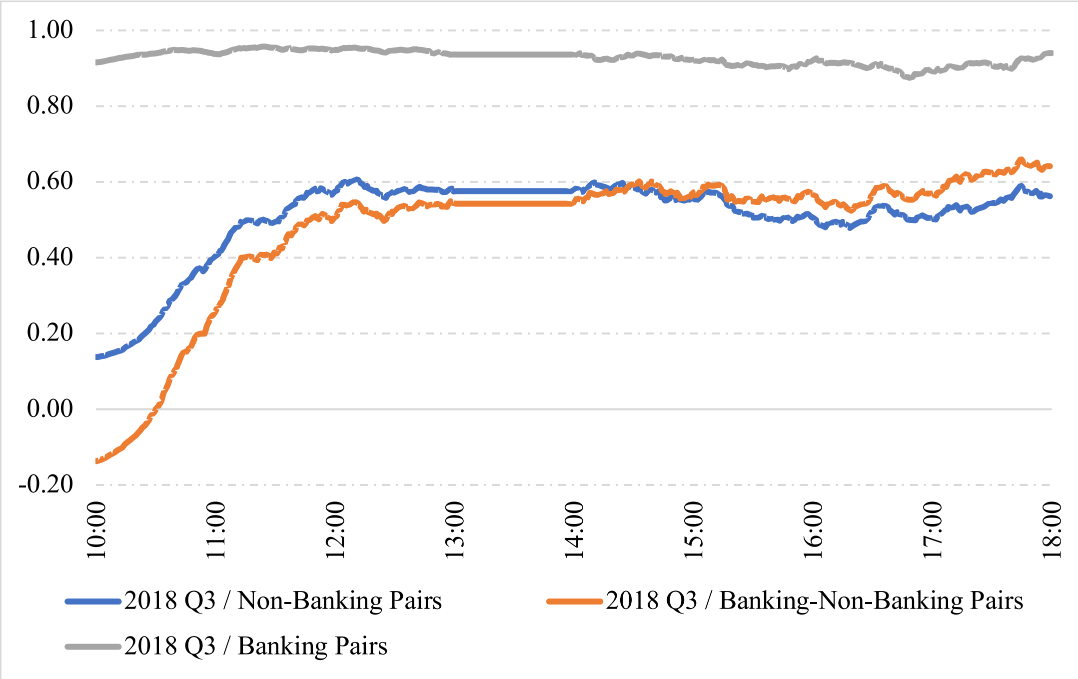

Figure 21. Comparison of average conditional correlations across different stock-pair groups for the entire study period of 2018 Q3

5.2 Day-of-the-week effect

Day-of-the-week differences are checked via Dynamic Time Warping (DTW) by comparing time series pairs of each day. Even though DTW was originally designed for voice recognition, it is now widely used in different fields as a similarity measure. To gauge the alikeness between time series with equal or differing lengths, DTW checks the best alignment via coupling one point in one of the series with one or more points on the other series. In contrast to Euclidean method in which the distancing is conducted in a pairwise fashion, a distance matrix is constructed to reach the best global alignment between the time series by looking additionally at the previous computations. As stated, average correlation figures are stored as time series for all days and averaging operation is conducted for all forty-five stock-pairs and for groups comprised only of banking, non-banking or banking/non-banking shares. Respective DTW outputs are reported in Table 3, Table 4, Table 5 and Table

6. Results show that evolution of overall conditional correlation figures are similar for Mondays, Tuesdays and Fridays. Visual inspection for graphical similarity is supported by DTW distance numbers for each day pair as well.

Table 3. Dynamic Time Warping Distance Measures - 45 Pairs of All 10 Stocks

All Stock Pairs	Mondays	Tuesdays	Wednesdays	Thursdays	Fridays
Mondays	-	468.88	612.98	749.94	371.50
Tuesdays		-	348.84	471.45	329.01
Wednesdays			-	370.37	519.22
Thursdays				-	591.62
Fridays					-

Table 4. Dynamic Time Warping Distance Measures - 10 Pairs of 5 Banking Stocks

Banking Stock Pairs	Mondays	Tuesdays	Wednesdays	Thursdays	Fridays
Mondays	-	294.79	188.65	683.06	490.30
Tuesdays		-	230.23	213.91	210.69
Wednesdays			-	414.85	251.94
Thursdays				-	499.78
Fridays					-

Table 5. Dynamic Time Warping Distance Measures - 10 Pairs of 5 Non-Banking Stocks

Non-Banking Stock Pairs	Mondays	Tuesdays	Wednesdays	Thursdays	Fridays
Mondays	-	992.27	996.74	1108.99	371.83
Tuesdays		-	526.23	512.24	511.00
Wednesdays			-	441.17	441.38
Thursdays				-	591.29
Fridays					-

Table 6. Dynamic Time Warping Distance Measures - 25 Pairs of 5 Banking and 5 Non-Banking Stocks

Banking / Non-Banking Stock Pairs	Mondays	Tuesdays	Wednesdays	Thursdays	Fridays
Mondays	-	449.94	840.73	856.42	450.83
Tuesdays		-	847.76	614.05	493.88
Wednesdays			-	444.61	524.90
Thursdays				-	734.24
Fridays					-

Regardless of stock-pairs segmentation, nearly first two hours of a typical trading day is marked with rising correlation for all groups. This trend is solid on every weekday and even steeper on volatile market conditions. When DTW is run just for the first two hours of a day, acquired distance numbers are more akin to each other in Monday-Tuesday, Tuesday-Friday, Wednesday-Friday, and Thursday-Friday pairs. Likewise, visual inspection reveals that conditional correlation numbers' reaction to US market openings are more overt on Mondays, Tuesdays and Fridays and DTW results evince that day pairs which include Wednesdays or Thursdays go with higher distance outputs almost in all the pairs. The DTW statistics are tabulated in Table 7 and Table 8.

Table 7. Dynamic Time Warping Distance Measures for the First 2 Hours of Each Weekday- 45 Pairs of All 10 Stocks

All Stock Pairs	Mondays	Tuesdays	Wednesdays	Thursdays	Fridays
Mondays	-	57.47	63.11	187.88	127.36
Tuesdays		-	22.17	58.01	34.97
Wednesdays			-	47.30	36.81
Thursdays				-	47.37
Fridays					-

Table 8. Dynamic Time Warping Distance Measures for the Period 16:30-18:00 on Each Weekday-45 Pairs of All 10 Stocks

All Stock Pairs	Mondays	Tuesdays	Wednesdays	Thursdays	Fridays
Mondays	-	174.91	375.68	524.28	231.38
Tuesdays		-	116.41	433.56	40.32
Wednesdays			-	285.09	88.16
Thursdays				-	433.83
Fridays					-

5.3 Epps effect

The aforementioned Epps Effect reveals valuable insights on the behavior of covariance or correlation dynamics for interested parties of finance community. As Epps (1979) documented decades ago, unconditional co-movements vary depending on the measurement frequency. Hence, one needs to be careful about the adopted procedure. Also, one of the critical facets of empirical outcomes is related with the stock pairs. Whether each item in pairs belongs to the same sector or not plays a significant role on the magnitude and dynamics of the correlations across different time intervals. For the same sector, correlation does increase in gradually larger intervals whereas it plateaus after 5-minute intervals and starts declining as intervals get wider when the pairs are from different sectors.

Awareness of Epps Effect is crucial for portfolio managers, risk managers and certain investor profiles. If the investment horizon is quite short and the aim is a diversified portfolio construction for instance, forming it based on the figures of unconditional correlations that are calculated with time series of daily returns may not provide the desired diversification or may result in missing out far more positive returns that would have been enjoyed otherwise.

Correlation numbers are stored for five seconds, ten seconds, thirty seconds, one minute, five minutes, ten minutes, twenty minutes, thirty minutes, one hour, two hours, three hours, one day and two days return series. Numbers in the time series are the percentage changes of log prices between respective intervals. In case there is no quoted price for the a given time stamp, previous tick rule is applied to fill in the data set as applied in Epps (1979). Figure 22, Figure 23 and Figure 24 are constructed for banking stocks pairs and show how correlation changes depending on the data construction intervals.

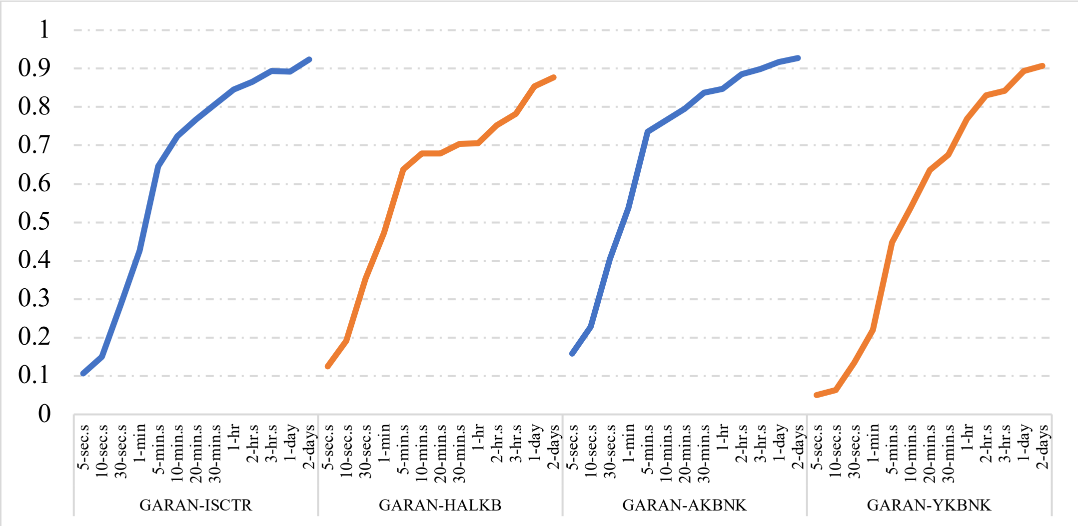

Figure 22. Epps Effect for banking stocks pairs - I

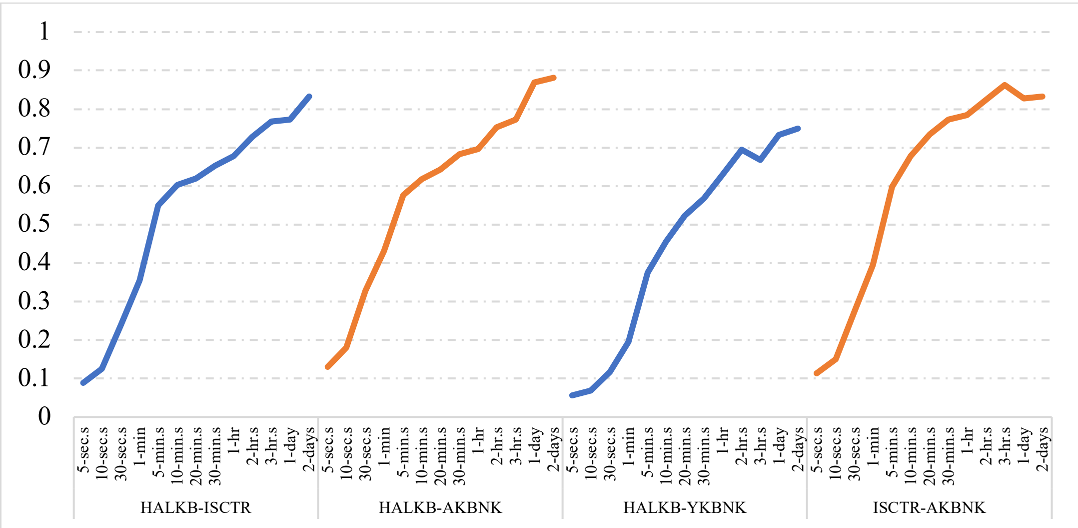

Figure 23. Epps Effect for banking stocks pairs – II

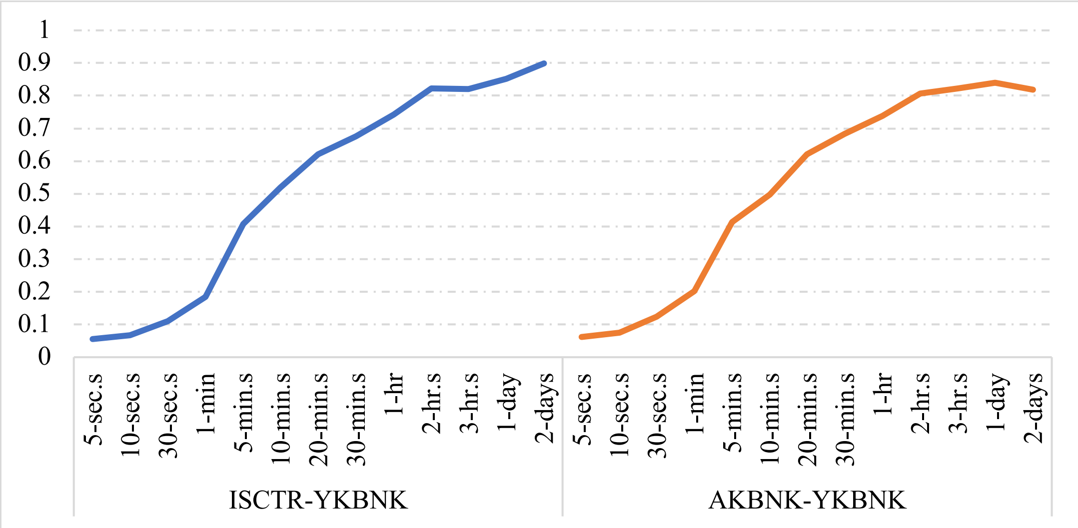

Figure 24. Epps Effect for banking stocks pairs – III

In Figure 25 to Figure 33, graphs depict the evolution of correlations across different measurement intervals for pairs of the stocks from different sectors. A profound look into the correlation patterns proves differing behaviors for different pairs. Some of the pairs even start in positive correlation, climb to higher levels and end-up in negative numbers. However, in all of the pairs, correlation numbers increase as the time series construction intervals get larger up to ten minute-interval lengths.

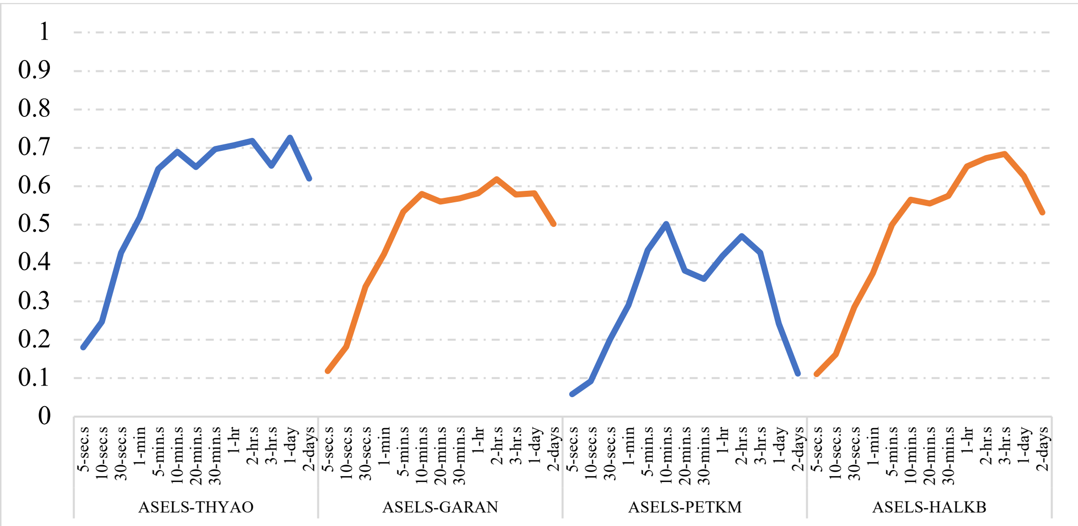

Figure 25. Epps Effect for pairs of stocks from different sectors – I

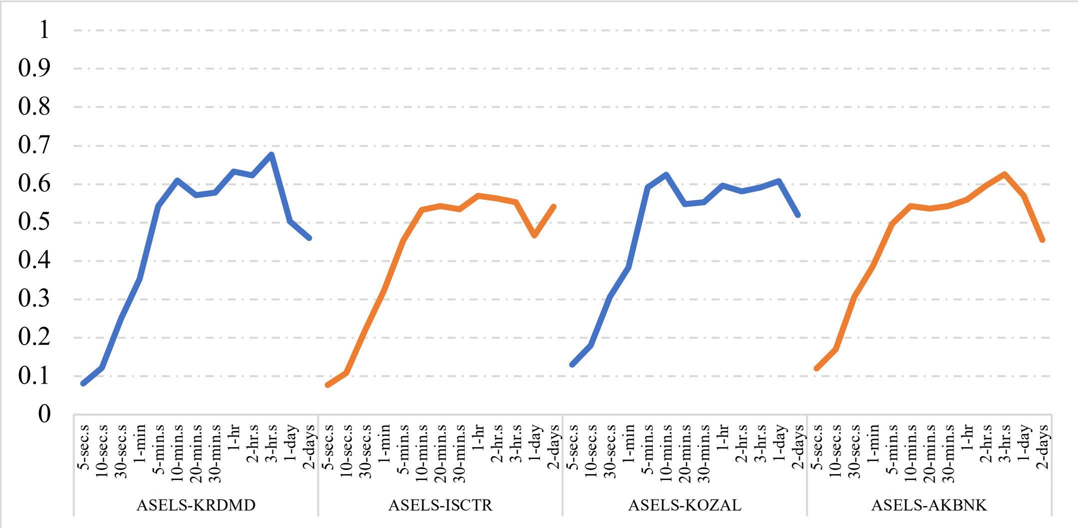

Figure 26. Epps Effect for pairs of stocks from different sectors – II

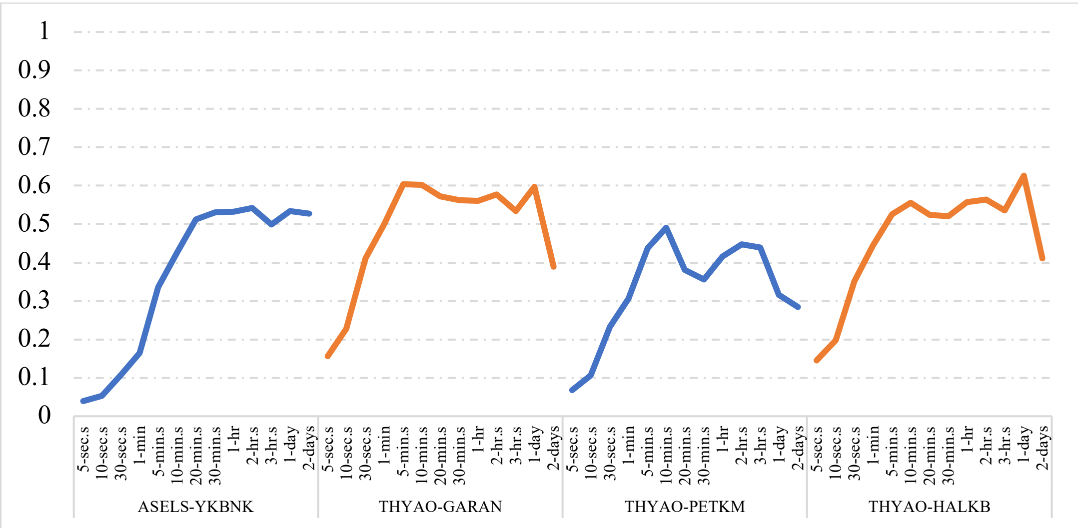

Figure 27. Epps Effect for pairs of stocks from different sectors – III

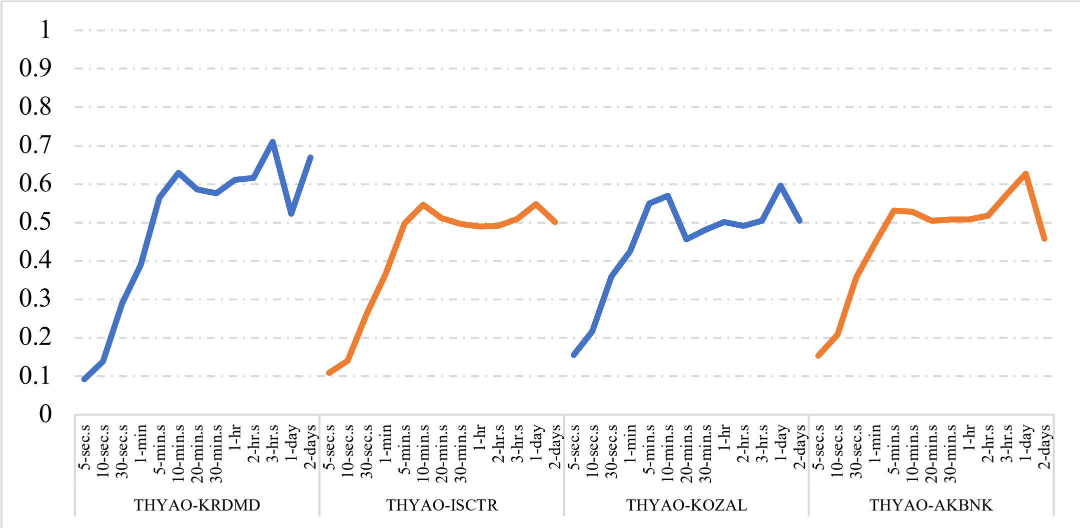

Figure 28. Epps Effect for pairs of stocks from different sectors – IV

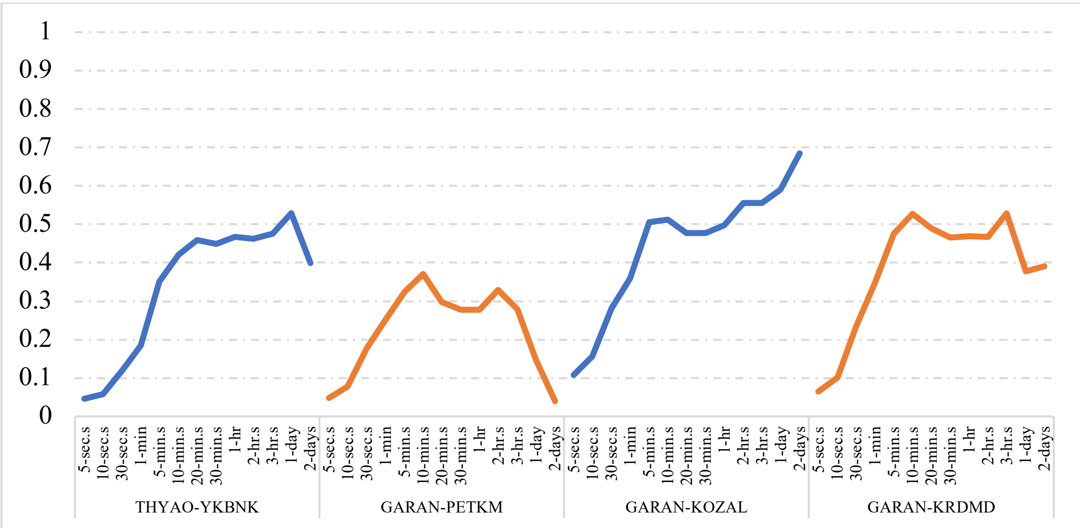

Figure 29. Epps Effect for pairs of stocks from different sectors – V

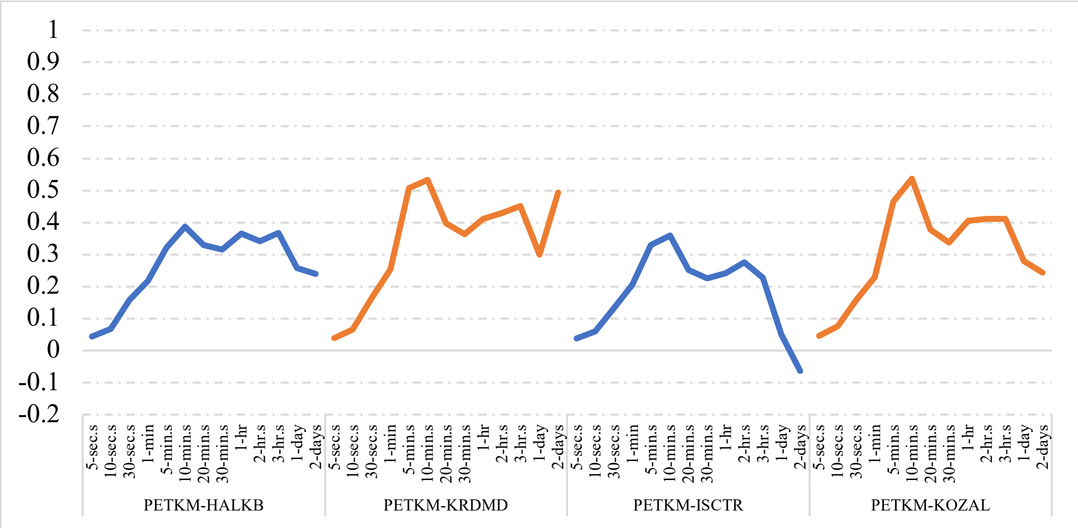

Figure 30. Epps Effect for pairs of stocks from different sectors – VI

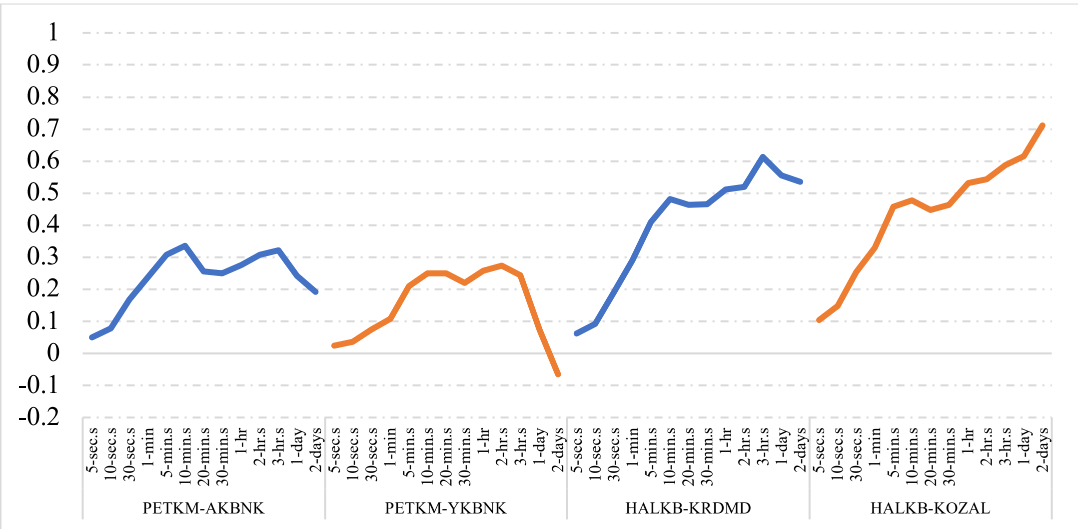

Figure 31. Epps Effect for pairs of stocks from different sectors – VII

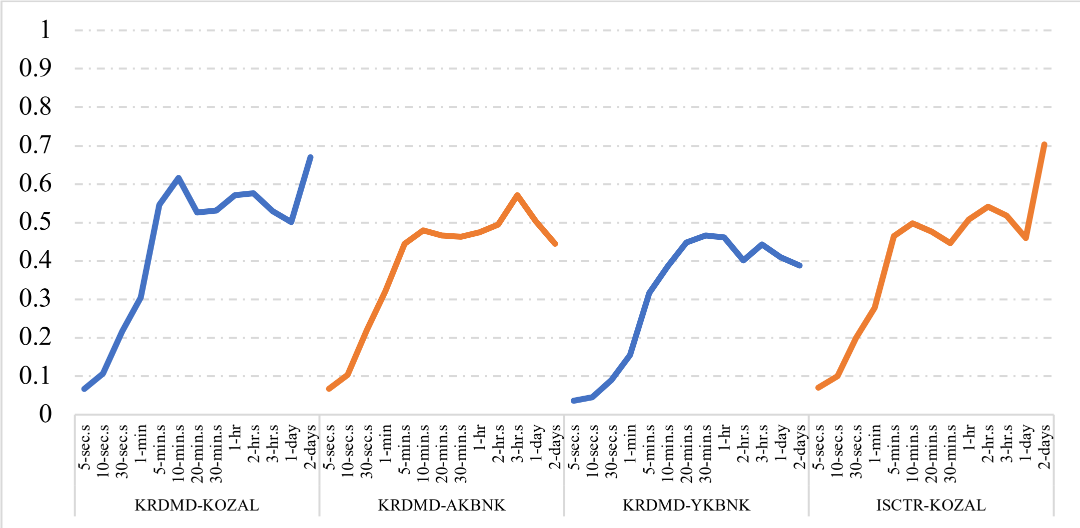

Figure 32. Epps Effect for pairs of stocks from different sectors – VIII

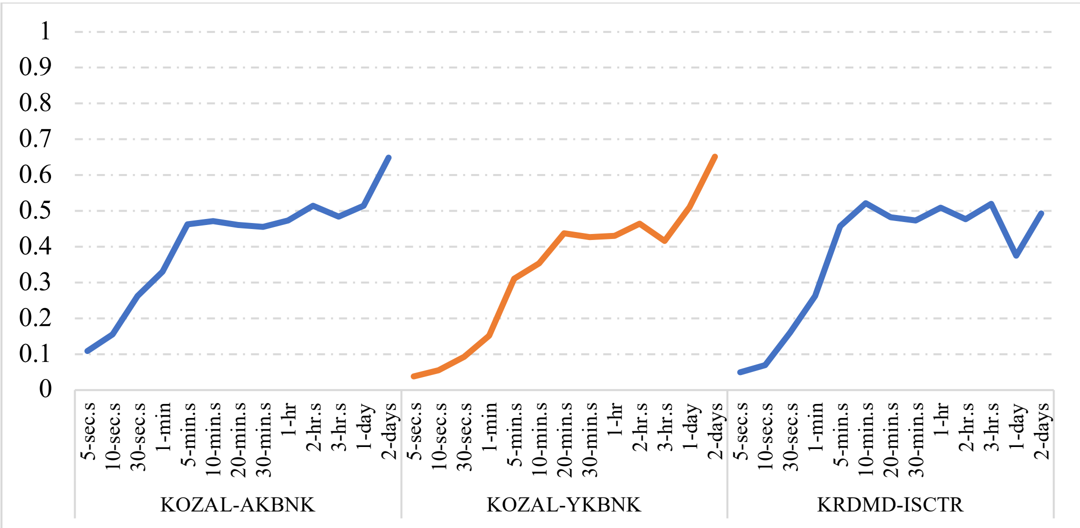

Figure 33. Epps Effect for pairs of stocks from different sectors – IX

CHAPTER 6

CONCLUSION

Co-movement of asset prices is one of the most crucial determinants of portfolio performance. When measured in a dynamic time-dependent manner, degree of joint behavior among them deviates from its unconditional levels, revealing valuable information that should govern market participants' behavior. Classical methods underestimate the correlation levels on intraday level due to complications arising from asynchronicity and microstructure noise. Therefore, sophisticated day-traders, high frequency traders and near real-time risk management professionals would be misguided with the outputs. In that regard, combination of GAS and state-space modelling used in this study rectify the main drawbacks of classical correlation measurement methods.

Main motivation behind this dissertation was to employ a state-of-the-art method in estimating intraday conditional correlations in an emerging market and assess if they evolve differently than those in a developed country. The dynamics are investigated to document seasonality; to detect if there is a day-of-the-week effect and further to reveal any differences in various market conditions.

The findings of this study on intraday seasonality reveal that average correlation figures at Borsa Istanbul equity market climb in the first 2 hours of trading and hovers around certain levels before rising further at the end of the trading day. Driving forces behind overall daily pattern are of two-legged; idiosyncratic and market-related. Accumulated overnight information and firm-specific events are reflected to prices by market participants shortly after the market opening in the morning. However, the market forces come to dominate pricing mechanisms as the trading day continues.

Although numbers dived before the closing bell in New York Stock Exchange as Buccheri et al. (2020) shows, last section of a trading day at Borsa Istanbul is marked with upward movement on average. In other words, during the period when both markets are open, there is visible and measurable change in conditional correlation path of Borsa Istanbul Equity Market after the time US Markets open. This is particularly overt on Mondays, Tuesdays and Fridays. Hence, for emerging markets, intraday conditional correlation dynamics cannot be evaluated in isolation with developed markets' spillover effects.

Day-of-the-week effect is visually identifiable for Mondays, Tuesdays and Fridays in which dynamic correlations distinctively start rising around 16:30. Dynamic Time Warping results support this and reveal analogous intraday conditional correlation patterns for those days. Findings also show concerted market action during market turmoil as the correlation hits higher levels in those periods.

Regarding the Epps Effect, which simply means changing unconditional correlation numbers depending on the adopted methodology in time series construction out of which these unconditional correlations are calculated, it is still existent, and shape of the unconditional correlation path differs according to the stock-pairs being comprised of same sector stocks or not.

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