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RESEARCH ARTICLE

EPPS EFFECT STILL EXISTENT: DIFFERING UNCONDITIONAL CORRELATION BEHAVIORS FOR INTER-SECTOR STOCK PAIRS

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ABSTRACT

For diversification purposes, investors may well distribute their investment budgets to different assets. Degree of co-movement between these assets is one of the critical determinants of portfolio performances. An investment strategy that favors putting the assets -of which the prices are driven by the same underlying factors- into to the same basket will be vulnerable to negative shocks. As the number of assets in an investment bundle grows, variance risk gradually fades whereas the covariance risk still lasts. In that regard, correlation numbers become significant. Measured correlation figures on the other hand differ as the adopted methodology for correlation calculation varies. As the time series of interest are constructed with narrower intervals for a given period, correlation numbers decrease almost all the time. This is called as Epps Effect in the literature and non-synchronicity and lead-lag relationships were shown to be main causes behind the scene. This study displays how correlation numbers continue rising as the measurement intervals gets larger for stock pairs of the same sector even though this is not the case when pairs are formed with the stocks of different sectors. Although trading practices and market dynamics changed tremendously, and algorithms took over considerable share in trading volumes, this study sheds light on the on-going existence of Epps Effect in an emerging market exchange in spite of the recent technological improvements in various layers of investment cycle.

Keywords: Epps Effect, Unconditional Correlations, Diversification

1. INTRODUCTION

Correlations among financial assets and its dynamic nature strongly affect investment practices, risk management operations and market expectations. Bollerslev (1990) introduced Constant Conditional Correlation (CCC) model whereas Engle (2002) more recently unveiled dynamic conditional correlation in his DCC GARCH model. Monitoring correlation patterns in a non-static fashion requires sophisticated model construction as done in Engle (2002) or quite newly in Buccheri et al. (2020). However, rather than instantaneously measuring correlation magnitudes, a researcher sometimes needs unconditional correlation levels as the global statement for the level of co-movement to be used in other respective studies. At this point, applied methodology becomes significant and can strongly affect the outcome as figured out in Epps (1979). In his paper, Thomas Epps showed how correlation numbers reverted to higher levels as the data -on which the correlations are calculated- is constructed with larger time intervals.

Later on, causes of the Epps Effect are deeply studied and non-synchronous trading and lead-lag effect were addressed to be the main ones in academic literature. Increased trading activity had been predicted to be eradicating non-synchronicity over years but Toth and Kertez (2009) still detects Epps Effect in spite of the decreasing average duration between trades. Additionally, different reaction times to same market news keep lagged price movements for some stocks still alive. Authors also find different asymptotic correlation levels for different years and attributes this to prevailing economic factors and sector-wise happenings in corresponding time periods.

This paper tries to shed light firstly on the unwavering existence of Epps Effect despite all technological improvements in trading business and diversified information channels. Study further aims to extend previous findings by drawing attention to correlation swings and convergence paths by sector groupings. To the best of my knowledge, this is also the first study which analyzes Epps Effect in Turkey. Section II includes literature on Epps Effect. Data and methodology are presented in Section III. Empirical findings are presented in Section IV. Section V concludes.

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2. LITERATURE

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 time series constructed with 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-minutes 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.

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) touches upon frequency differences in trades of different stocks and builds 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 and 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 auto-correlation. This non-trading problem will bias the econometric results if not considered.

Bonanno et al. (2001) selects one-hundred stocks from US equity markets for the period January 1995- December 1998 and constructs 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 converts 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 shortens 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 made the most of Monte Carlo simulations and hypothesized 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 concluded those two factors are the main reasons of declining correlations with higher frequency and presented an evidence from his analysis on DEM-USD and JPY-USD exchange rates data. With simultaneous quotes, Epps effect was eliminated to some extent although not eradicated completely. He calculated 8 seconds of lead-lag relationship in the data pair and reanalyzed his findings by shifting one of the data series 8 seconds to secure synchronicity. This operation substantially decreased the Epps effects and made 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 gave similar results- lag period this time being 70 seconds.

Asynchronicity in trades is one of the mostly uttered causes of correlation decreases for shorter time windows. As the trading activity is accelerated, number of contemporaneous price pairs will be increasing and that would inhibit the correlation magnitudes falling further down as the time intervals get narrower. This was shown theoretically via Monte Carlo simulations in Reno (2003). Toth and Kertesz (2009) this time however discusses that empirical findings for higher trading activity suggest not to be so straightforward about the alleged achievements of active trading on fixing the flaws of correlation numbers for high-frequency intervals. In order to sterilize their findings on synchronicity, Toth and Kertesz (2009) focuses on stocks where lead-lag relationship is ignorable. In that regard, Coca Cola/PepsiCo, Caterpillar/ Deere, Wal-Mart Stores/Sprint Nextel Corp. etc. are taken for deeper analysis. Correlation structure (dependent of sampling timescale) of Coca Cola/PepsiCo pair for the period 1993-2003 is printed for visual inspection and displayed to increase as the time interval gets larger to reach out its asymptotical value. More interestingly, this correlation coefficients are graphed separately for the years 1993, 1997, 2000 and 2003 which converge to different correlation levels as the timescale is enlarged. Although correlation numbers of 2003 are above those of 1993 at the very short time intervals for instance, figures for both years start to increase as the time interval gets bigger. Toth and Kertesz (2009) scales the correlations of the years 1993, 1997, 2000 and 2003 with their asymptotic values and curves this time nearly overlaps in all timescales with concave shape of correlation figures still existent. Hence authors conclude that level of trading activity, as asserted in their earlier study, cannot be responsible for the Epps Effect solely and points out some other more reasonable factors shaping the pattern; most probably the reaction times of humans. Later, Toth and Kertesz (2009) divides time concept into three market time scales: frequency of trading in the market (market activity), market periodicities and reaction time of traders to news and events. First two were shown to be not bringing a satisfactory explanation in Toth and Kertesz (2009). Regarding the last one, it will be a highly optimistic expectation for investors to react instantly to newly arriving information. There are studies showing that prices absorb disclosed information within first fifteen minutes after it is released. Chordia et al. (2008), Busse and Green (2002) and Barclay and Litzenberger (1988) are among many others.

3. DATA AND METHODOLOGY

Data consists of tick-by-tick trades of highly liquid XU030 index stocks in Borsa Istanbul equity market and listed in Table 1. Prices are stored for the third quarter of 2018. Even tough Epps (1979) applies 10 minutes intervals as the narrowest intervals, this study shortens it even to 5-second long intervals. Also, as is known, there may be more than one trades which coincide on the same second. In other words, there are trades on sub-second levels. Following Barndorff-Nielsen et al. (2009), median of these trades are taken as the sole price quotation for that second.

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 quarter 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 reports this co-movement when stocks are put into certain index and touches upon the factors of "friction-based" convergence. Even though days are analyzed separately in the study, requirement of index membership before and after the third quarter of 2018 eliminates these latent drivers in correlation structure.

Table 1. Stock Tickers and Company Names

Ticker Symbol	Company Name
ASELS	Aselsan
THYAO	Turkish Airlines
GARAN	Garanti Bank
PETKM	Petkim Petrochemistry
HALKB	Halkbank
KRDMD	Kardemir (Group D)
ISCTR	Is Bank (Group C)
KOZAL	Koza Gold
AKBNK	Akbank
YKBNK	Yapikredi Bank

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.

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).

4. EMPIRICAL FINDINGS

Findings reveal valuable insights for interested parties of finance community. Unconditional hand-in-hand movements vary depending on the methodology chosen as pictured in Epps (1979) decades ago. Hence, one needs to be careful about the adopted procedure. However, 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 determines the shape of correlation path. For the same sector, correlation does increase almost in all successive intervals whereas it makes plato after 5-minute intervals and starts mostly declining towards the largest intervals when items of 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 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.

Figure 1, Figure 2 and Figure 3 are constructed for banking stocks pairs and show how correlation changes depending on the data construction intervals.

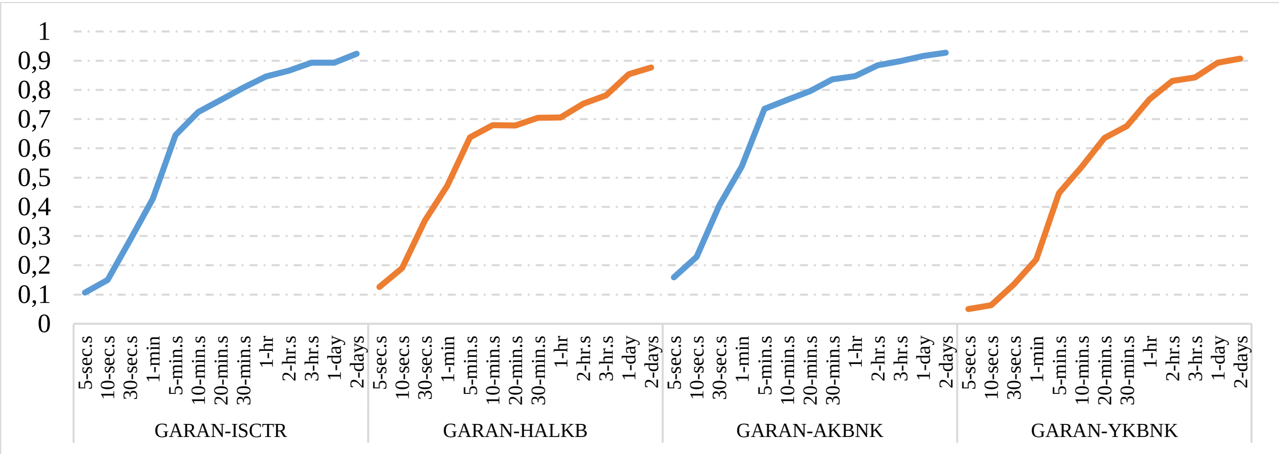

Figure 1: Epps Effect for banking stocks pairs - I

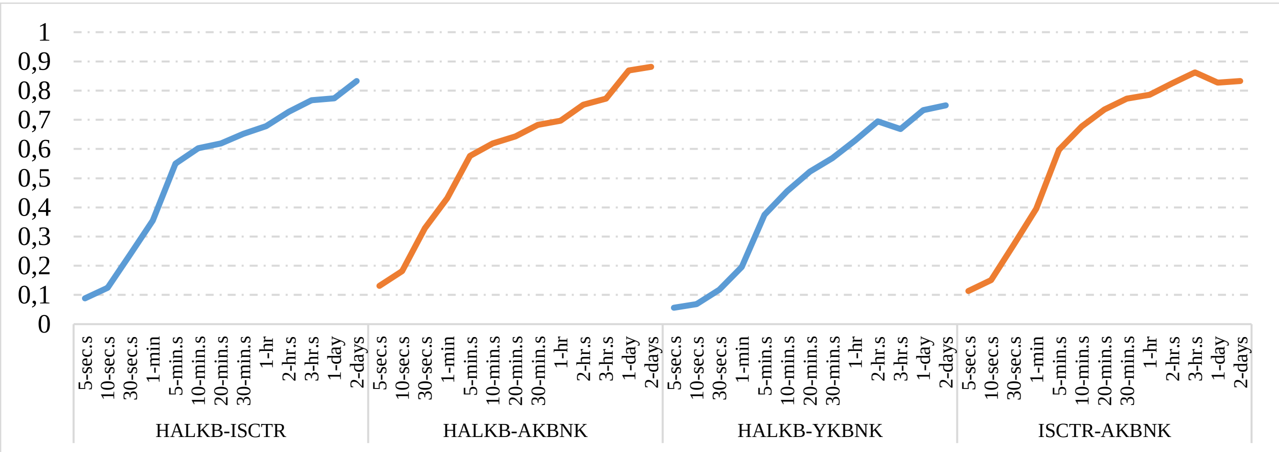

Figure 2: Epps Effect for banking stocks pairs - II

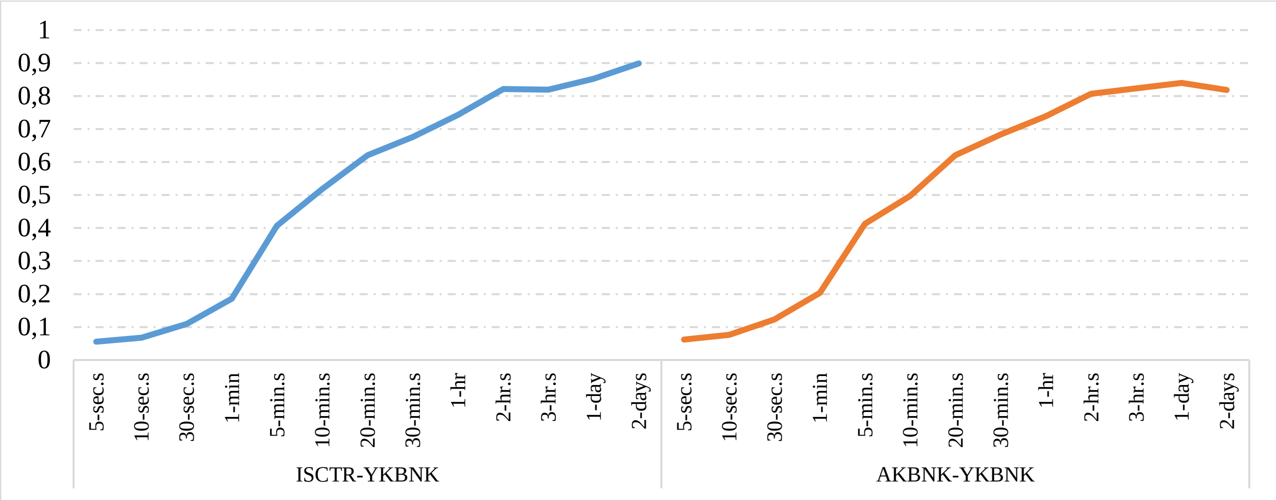

Figure 3: Epps Effect for banking stocks pairs - III

From Figure 4 to Figure 12, graphs depict the correlation path if stocks in the pairs are from different sectors.

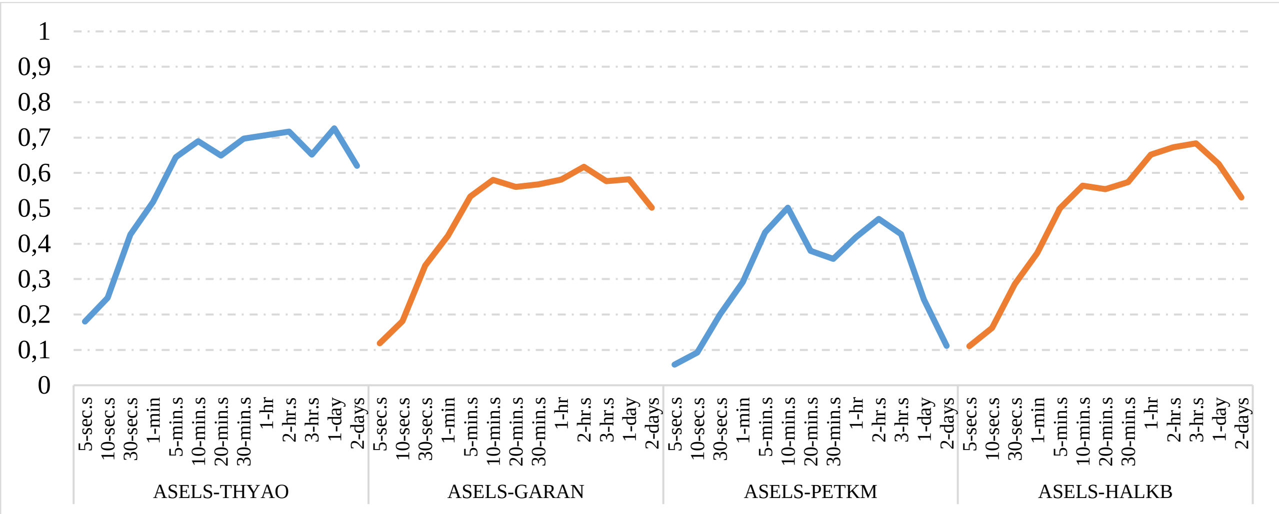

Figure 4: Epps Effect for pairs of stocks from different sectors - I

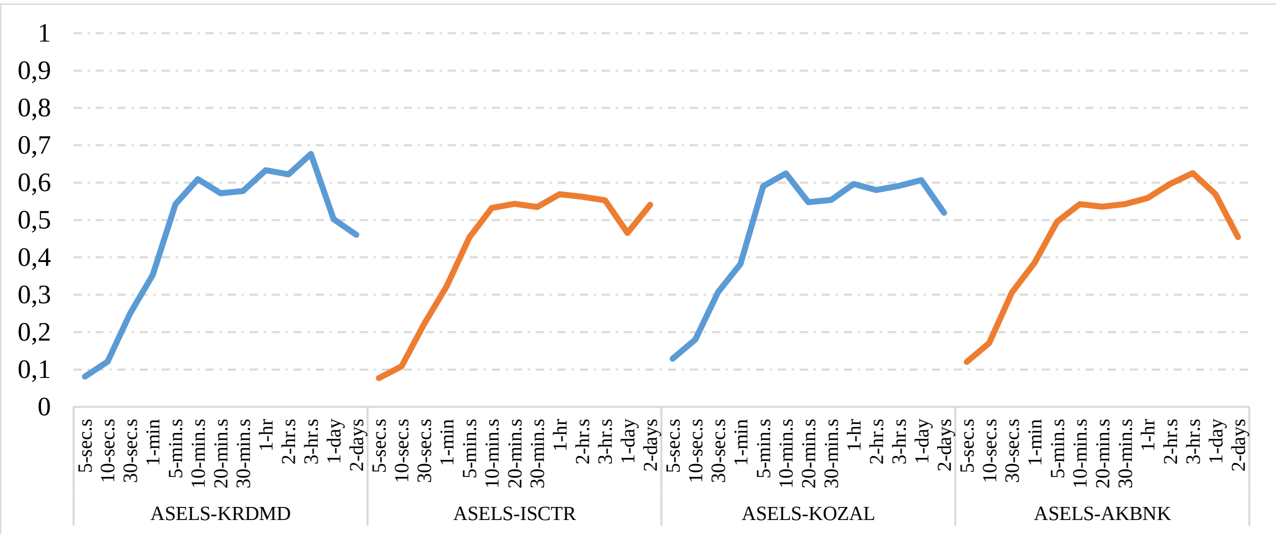

Figure 5: Epps Effect for pairs of stocks from different sectors – II

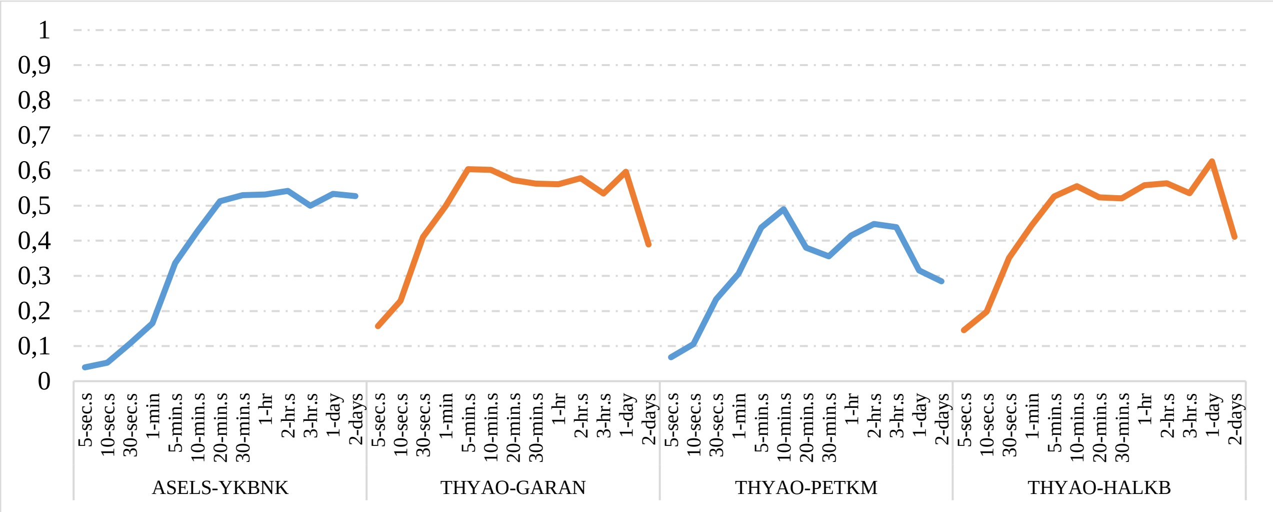

Figure 6: Epps Effect for pairs of stocks from different sectors – III

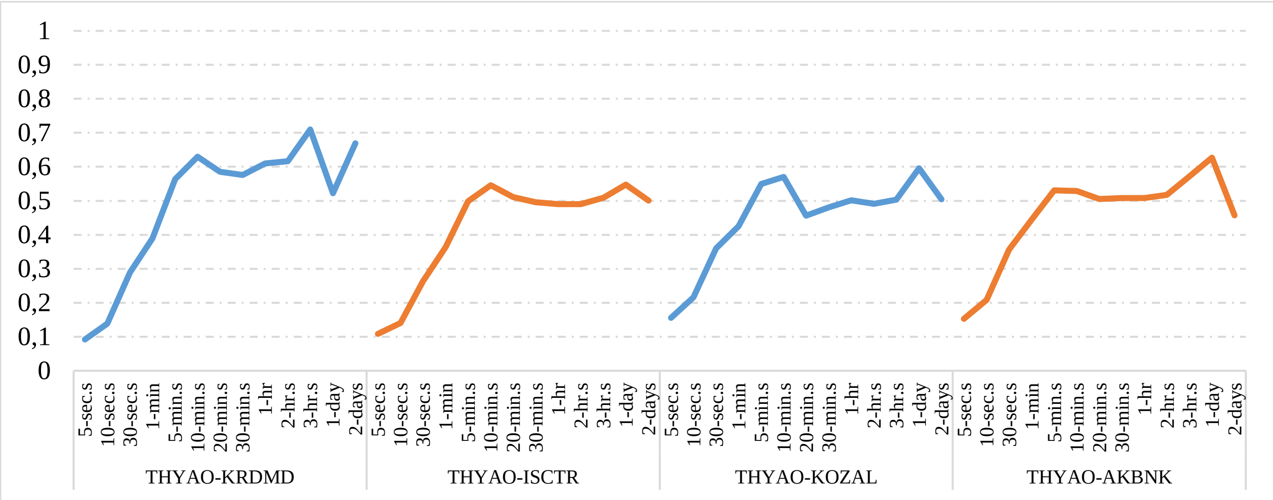

Figure 7: Epps Effect for pairs of stocks from different sectors – IV

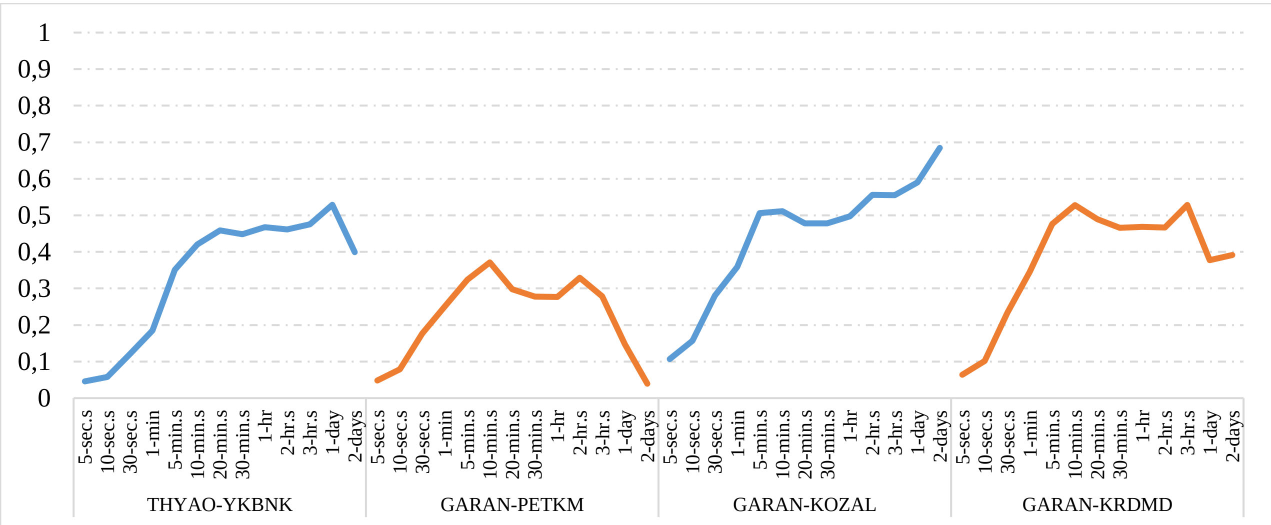

Figure 8: Epps Effect for pairs of stocks from different sectors – V

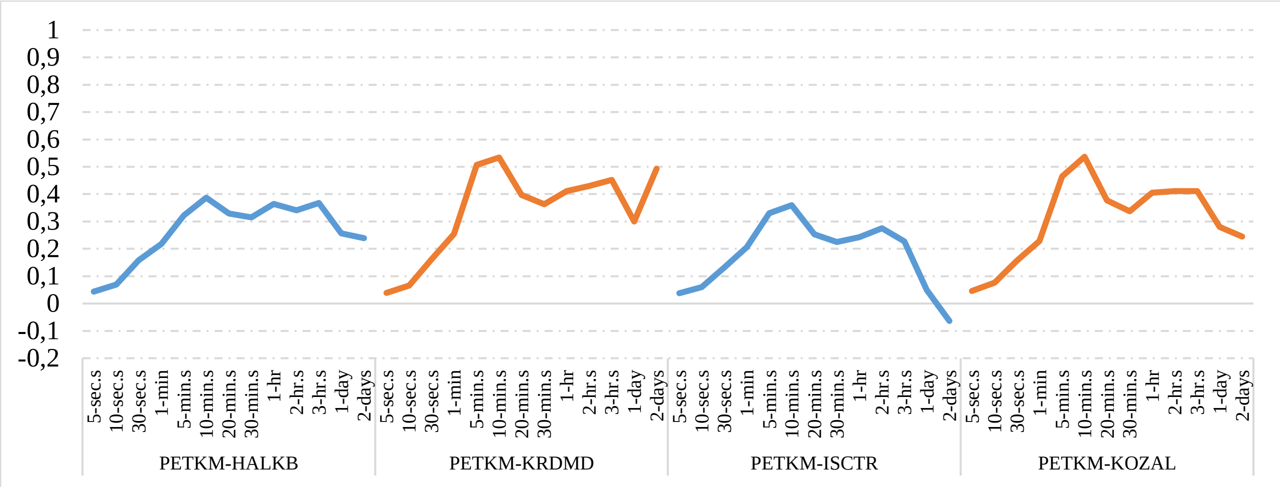

Figure 9: Epps Effect for pairs of stocks from different sectors – VI

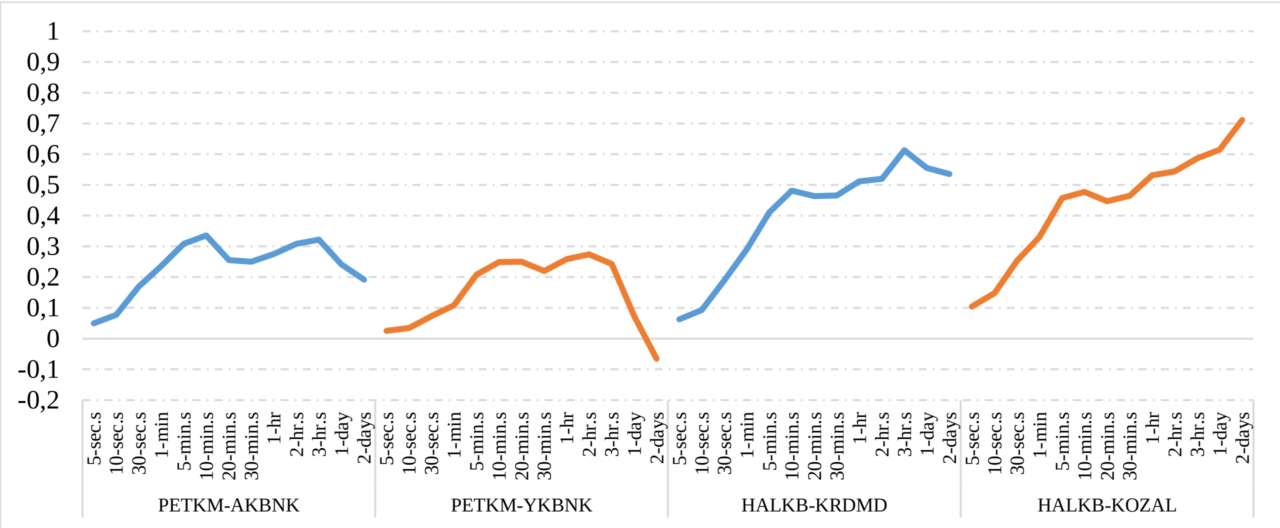

Figure 10: Epps Effect for pairs of stocks from different sectors – VII

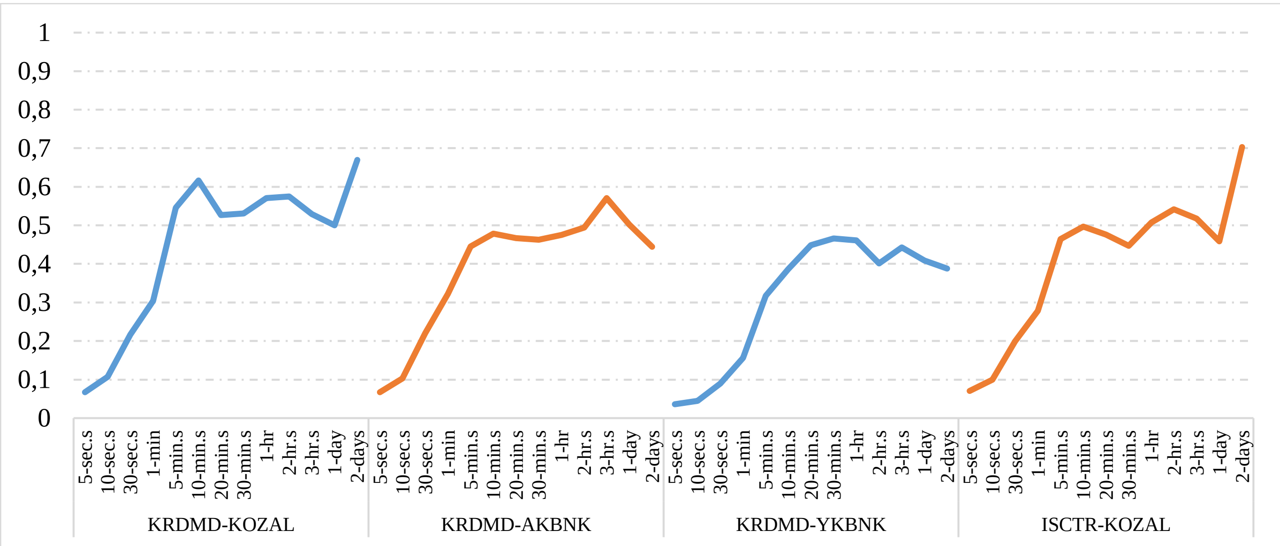

Figure 11: Epps Effect for pairs of stocks from different sectors – VIII

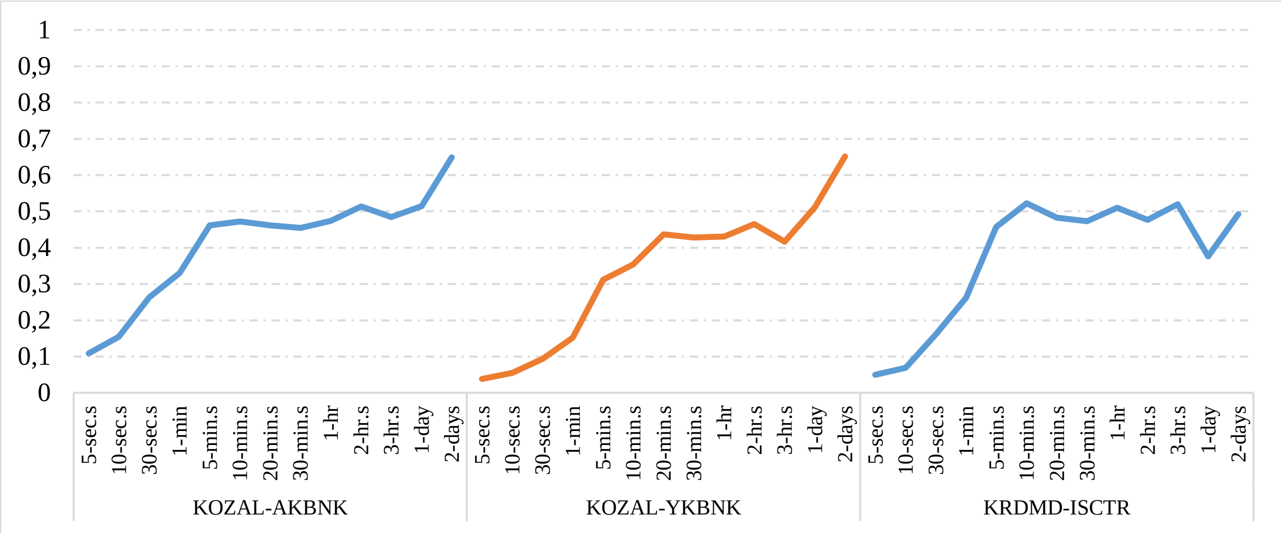

Figure 12: Epps Effect for pairs of stocks from different sectors – IX

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 at the beginnings as the time series construction intervals get larger.

5. CONCLUSION

Findings clearly proves the existence of Epps Effect after almost four decades from its first detection. This is the first study conducted for Borsa Istanbul stock exchange. Lead-lag effect and non-synchronous trading have been discussed to be the main causes behind this phenomenon in the literature. Over the past years, technological improvements in trading business, breakneck speed in news disclosure and data processing, agility brought by powerful trading tools like algorithms and pertinent infrastructure have been expected to lessen the lead-lag periods. Additionally, increased trading activity is a kind of treatment for non-synchronicity. Despite all the transformations, Epps Effect preserves its existence. Generally speaking, results indicate rising correlation numbers as the time series of returns are built by larger intervals. Other crucial finding is the distinction between inter-sector and intra-sector stock pairs; correlation numbers continue rising even up to two-day intervals in the pairs of banking stocks although numbers fluctuate and mostly decrease after three-hour intervals for intra-sector pairs. Hence, one needs to be careful about the mismatch of selected interval for constructing unconditional correlations and the essence of his/her research.

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