ARAŞTIRMA MAKALESİ / RESEARCH ARTICLE

ANALYZING TIME-FREQUENCY NEXUS BETWEEN STOCK RETURNS AND BOND YIELDS THROUGH WAVELETS: THE CASE OF TURKEY – PART I[*]

HİSSE SENEDİ GETİRİSİ VE TAHVİL GETİRİSİ ARASINDAKİ ZAMAN-FREKANS BAZLI İLİŞKİNİN DALGACIKLAR YÖNTEMİYLE ANALİZİ: TÜRKİYE ÖRNEĞİ – BÖLÜM 1

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Abstract

This paper reinvestigates the stock-bond nexus using 605 weekly observations of stock index prices and the 2-year benchmark rate of Turkey over a sample period covering April 1, 2005, and December 30, 2016. By conducting a novel approach, wavelet analysis, we aimed to offer a deeper understanding of the relationship considering the investor's heterogeneities on investment periods. The results show weekly positive averages for all stock index returns but negative average for bond yields over time. Wavelets variance analysis reveals that the higher scale the lower volatility, namely, the most of fluctuations in returns is explained by short-term, suggesting that short-term investors should react to every fluctuation in their asset returns. Similarly, the stock market is found to be more volatile than the bond market. As expected, test findings highlight significantly negative stock-bond linkage. Wavelet cross-correlation results show significantly both positive and negative bidirectional causal linkages over higher wavelet-scales.

Keywords: Wavelets, lead-lag, wavelet variance, correlation, and cross-correlation.

Jel Codes: C14, C40, E43, E44, G12

Öz

Bu çalışmada 2005-Mayıs ve 2016-Aralık dönemine ait 605 haftalık borsa fiyat endeksleri ve 2-yıllık tahvil faizi kullanılarak tahvil-borsa ilişkisi araştırılmıştır. Literatürde kabul gören ilişki türü, piyasalarda farklı yatırım dönemlerine sahip yatırımcıların varlığı göz önünde bulundurularak son yıllarda sıklıkça kullanılan dalgacıklar yöntemi yardımıyla yeniden incelenme ihtiyacı doğmuştur. Elde edilen bulgulara göre hisse endeksleri pozitif, tahvil getirileri ise negatif ortalamaya sahiptir. Dalgacık bazlı varyans analizine göre ölçek sırası yükseldikçe getirideki volatilite azalmaktadır, diğer bir ifadeyle, getiri volatilitesindeki en yüksek payın kısa dönem değişmelerine ait olması, bu tür yatırım dönemine sahip yatırımcıların portföy kompozisyonunda gerekli hamleleri yapmasını gerektirmektedir. Borsa getirisindeki volatilitenin tahvil getirisindeki volatiliteden daha yüksek olduğu elde edilen bir diğer önemli sonuçtur. Diğer taraftan iki değişken arasında istatistiksel açıdan anlamlı zıt yönlü korelâsyon ilişkisi elde edilmiştir. Çapraz korelasyon bulgularına göre ise her iki değişken arasında hem zıt hem de pozitif yönde, özellikle yüksek ölçeklerde, çift taraflı anlamlı nedensellik ilişkisi bulunmaktadır.

Anahtar Kelimeler: Dalgacıklar, nedensellik, dalgacık varyansı, korelâsyonu ve çapraz korelâsyonu.

Jel Kodu: C14, C40, E43, E44, G12

Introduction

Although it has been long debated by researchers and regulators so far, the assessment of the co-movement between stock and interest rate is of great interest because changes in interest rate are one of the most effective sources of uncertainty about valuations of two major asset classes. Similarly, interest rate fluctuations are also of high importance for investment decisions to obtain optimal risk-return trade-off, asset valuation, and portfolio asset allocations. In finance theory, the dividend discount theory suggests that an asset value is determined by cash flows that the firm expected to generate in the future. Indeed, in order to find the current (market) value of an asset, the stream of future cash flows is discounted by an appropriate required rate of return. In this regard, bond and stock price will be more sensitive to fluctuations in discount rates that depend on the expectation of interest rate and risk premiums in the future.

It is widely accepted a knowledge that changes in interest rate have significant effects on both financial and nonfinancial firms' value and their earnings. The financial theory posits that the value of a financial firm is influenced by two main channels. A bank's value, for example, is very sensitive to interest rate movements through their balance sheet compositions and maturity mismatch of assets and liabilities. The latter argument is related to a fact that their balance sheets include nominal and frequently fixed-rate financial assets and liabilities, which their market value persistently varies whenever interest rate changes. The former argument, on the other hand, is related to a fact that financial firms confront with collecting short-term liabilities and funding long-term loans, therefore, causing maturity gap and significant interest exposure on the present value of assets and liabilities. The effects of interest rate movement are also true for nonfinancial firms' value through rising (decreasing) their cost of capital and decreasing (rising) stream of expected cash flows as well as affecting their market value of asset and liabilities.

According to the aforementioned arguments, it is expected that the stock price of both financial and nonfinancial firms will be predominantly sensitive to changes in interest rates. The main

question is what should be the direction of the relationship between those two variables. According to papers' results, there seems to exist both negative and positive relationship between stock returns and changes in bond yields. In theory, there should be a negative association. An illustrative list of papers that claim an adverse linkage includes Flannery and James (1984), Campbell (1987), Bae (1990), Thorbecke (1997), Elyasiani and Mansur (1998), Chen et al. (1999), Gulko (2002), Ilmanen (2003), and Connolly et al. (2005) for the U.S.; Dinenis and Staikouras (1998) for the UK, Gjerde & Sættem (1999) for Norway; Li (2002) for G7 countries and Saporoschenko (2002) for Japan. Using weekly observations of commercial banks' stock prices and Treasury bond yields, Flannery and James (1984) point out that common stock returns are very sensitive to changes in bond yields. The effect of interest rate depends on the maturity composition of net assets in the balance sheet. In line with the findings of Christie (1982) regarding the nominal contracting hypothesis, the maturity composition of nominal contracts has noteworthy impacts on common stock returns, namely, interest rates are positively connected to the volatility of equity returns, therefore, adversely related to equity value. Bae (1990) argues that changes in current and unexpected interest rates have significantly negative effects on stock returns of financial firms while the degree of long-term is more pronounced. On the other hand, stock returns of nonfinancial firms are found to be less sensitive to unexpected interest rate movements due to asset compositions. Furthermore, market values of financial firms are more rigorously affected by unexpected interest fluctuations than current interest rate fluctuations. Similarly, Dinenis and Staikouras (1998) find a negative relationship between the changes in interest yields and the common equity prices in the UK over January 1989 and December 1995 period. Furthermore, the effect of unexpected movement in interest rates is considerably higher for nonfinancial firms and volatility of interest rates is significantly positive for share returns of nonfinancial and financial firms. In a related paper, Thorbecke (1997) ascertains that innovations in monetary policy decisions have significantly affirmative impacts on ex-ante and ex-post share returns by decreasing the discount rate or increasing stream of future cash flows. In addition, monetary policy exerts large effects on small firms than large firms because its impact on access to credit is higher for the former firms. Chen et al. (1999) discover significantly negative effects from the unexpected announcements of discount rate movements and, however, an insignificant impact from expected changes to stock returns over a sample period January 1973 to January 1996. Gulko (2002) points out that bond and stock markets observe decoupling at the time of crisis, accordingly, a "flight-to-quality" phenomena is observed when implied volatility is high in markets. The author argues that Treasury bonds are recognized as the global safe haven asset because they provide effective diversification opportunities and enable investors to enhance their portfolio stabilities and resiliencies during financial turmoil. This evidence reinforces the argument made by Baur and Lucey (2009), who maintain that financial markets not displaying flights at the time of crisis suffer greater losses than markets with flights. Note that, the background behind those negative relationship results is explained by the discount factor in stock valuation. On the contrary, test findings of Li (2002) and Andersson et al. (2008) show that the negative stock-bond correlations stem from the uncertainty about inflation rates in the G7 countries and the U.S., Germany, and UK, respectively. Baele et al. (2010) underline the fact that liquidity proxies have a greater power on explaining negative stock-bond correlations among a variety of macroeconomic factors.

The argument presented for a negative relationship is discussed by Shiller and Beltratti (1992), who argue that it does not need to be right even though some implicit assumptions are valid. The main problem, however, is that the stream of cash flows for the bond is fundamentally different than that of dividend for stocks. Putting the same point in simpler terms, the former is reasonably in a nominal while, on the other hand, the latter is relatively stable in real terms. This differential stems from the high inflationary conditions that radically affect the discount rates for asset valuation. Since inflationary expectations are principally reflected in nominal long-term interest rates, its effect, therefore, will be limited for stock prices. Moreover, changes in long-term interest rates may convey information about the future stream of dividend payments. Misinformation about the outlook for corporate earnings might cause a positive association between stock prices and long-term bond yield, namely, negative relationship between stock-bond prices as observed on Black Monday in 1987. Therefore, a tendency for negative relation for bond yields and stock prices may be offset by the adverse information carried by changes in long-term rates. Similarly, Barsky (1989) remarks on the fact that both changes in stock prices and low real interest yields could be primarily explained by rising risk premium. A drop in interest rates, for example, could be a result of increased risk premium or/and precautionary savings, which, in turn, leads to a "flight to quality" phenomenon where investors shift their funds away from stocks to bonds. Johnson et al. (2013), on the other hand, ascertain that both cyclical (short run) and long-run correlation dynamics can vary due to several reasons. First, stocks and bonds classes may differently respond to changes in investor risk appetite, accordingly, a "flight to quality" may be observed in the short-term. On the other hand, both asset returns may be similarly influenced by macroeconomic factors in the long-term, therefore, similar effects could lead to an affirmative linkage. Second, the adverse beta between inflation and stocks may be less pronounced over longer periods since dividend growth rate by degrees reaches up to inflation. Lastly, a positive or less negative linkage may be observed due to overvaluation in asset prices, which is caused by FED policy decisions.

An illustrative list of papers in this field that documented evidence of significantly positive associations between stock returns and changes in bond yields includes Fama and French (1989), Schwert (1989), Titman and Warga (1989), Shiller and Beltratti (1992), Campbell and Ammer (1993), Fleming et al. (1998), and Stivers and Sun (2002). For example, Fama and French (1989) argue that expected excess nominal and real returns on stocks and corporate bonds are adversely related to business conditions. Moreover, these two variables are positively related each other, namely, they move in the same direction in the U.S. High bond and stock returns can be forecasted by the default spread and dividend yield when business conditions are persistently weak while the reverse (low returns) is true when conditions are strong. Shiller and Beltratti (1992) discover that the actual excess returns in the stock and bond markets are significantly positive related each other in both the full and postwar (1948-1989) samples, given that stock markets overreact to bond markets movements. However, they also report a correlation coefficient of "-0.40" for the U.S. and "-0.60" for the UK over time between the movements in actual long-term interest rate and the movements in actual real log equity prices. Schwert (1989) finds evidence of a positive association between the quality yield spread for corporate bonds and profitability with stock market volatility. Test results also document weak evidence for forecasting from macroeconomic volatility to financial asset volatility, while, on the other hand, the evidence is somewhat stronger for the reverse, indicating that new information related to economic

events the are rapidly incorporated into speculative asset prices. Moreover, falling stock prices relative to bond prices or financial leverage and the number of trading days are positively related to stock market volatility. According to test results of paper by Campbell and Ammer (1993), excess returns on long-term bonds and stocks are significantly positive related to each other in the periods of 1952-1987, 1952-1979, 1952-1972, and 1973-1987 due to varying expected future excess return rates, while for short-term bond is negative during the sample periods, ranging from "-0.065" to "-0.116". Stivers and Sun (2002), on the other hand, report a positive co-movement between stock and bond returns particularly when stock markets face lower uncertainty. Nonetheless, the correlation switches sign from positive to the negative direction or loses its strength throughout periods of high stock market uncertainty, offering diversification advantages for portfolio allocations between stocks and bonds. Furthermore, the lagged value implied Volatility Index (VIX) is found to be a good and useful indicator in explaining variation in the stock-bond return linkage. Rankin and Idil (2014) study the stock prices-bond yields correlation in the U.S., UK, Japan, and Australia and they find that they tended to be inversely related throughout much of the 20th century. Since the beginning of the 2000s, however, the correlation switches sign from negative to the positive direction in all markets, particularly, significantly rises during the global financial crisis. They conclude that relatively long period of positive relations is due to a substantial and persistent uncertainty about future economic activity created by the aforementioned crisis and innovations in monetary policy has significantly negative impacts on the correlation over time.

It is evident that findings are based on short – or/and long-term, not medium-term time horizon. It is also assumed that stock markets are homogenous in terms of investors profile, risk appetite, and expectations. Mainly, it is because of the Efficient Market Hypothesis' (EMH) unrealistic assumptions where it says that all investors have a similar expectation regarding risk-return tradeoff and similar investment horizon. However, as observed in the real world, it is not true. The Fractal Market Hypothesis (FMH) of Peters (1994) and the Heterogeneous Market Hypothesis (HMH) of Müller et al. (1993) are among the theories that disagree with the EMH. Both theories overall state that (i) financial markets are not homogenous but heterogeneous with many participants that have different time horizons, (ii) market participants with different investment horizons respond differently to information, i.e. pay attention only to suitable information regarding to their investment horizons, and (iii) both the long-term fundamental investing and short-term technical trading determine the market prices. Short-term trends in the market are predominantly stemming from crowd behavior activities, while, on the other hand, long-term trends are the result of changing economic environment. Fluctuations in short-term periods, therefore, will be more volatile than long-term trends.

There are two main causal tests based on frequencies: wavelets and frequency causality test introduced by Breitung and Candelon (2006). Broadly speaking, a time series or signal is decomposed into different time scale components by using wavelet transform. Providing the frequency and time behavior concurrently, wavelets make it possible to uncover the true dynamics of the relationship, which is hidden in the time domain, thereby, impossible by standard econometric methods. Scale based results are important because they are of interest to heterogeneous market participants, for example, intraday traders, monetary policy authorities, or long-term investors. As Graps (1995) states, wavelets give a chance to see both the trees and forest simultaneously. Moreover, as Schleicher

(2002) points out, it is possible to observe how investment horizons act relative to one another and reveal the structure of the time series at different time horizon. As mentioned above, the correlation relationship may also vary regarding the investment horizons because, as Harrison and Zhang (1999) contend, short-term investments are likely affected by changes in investor risk appetite, asset allocation decisions, or unanticipated consumption needs. Accordingly, the true relationship in the long-term may deviate from its equilibrium due to this short-time noise. In a related paper, Dajcman (2012) investigates the comovement between sovereign bond yields and equity returns linkages in Eurozone countries –Germany, Italy, Spain, Portugal, and Ireland– by employing a DCC-GARCH model. The findings reveal that comovement between markets displays a time-varying pattern. Except for Germany, all countries frequently observe a negative comovement during the European debt crisis of 2010-2011, namely, the flight-to-quality effect is only observed in Germany. Before 2010, however, all countries also show considerable flight-to-quality effects. Using monthly long-term bond yields and stock price data consisting of 537 observations for the U.S., France, and Canada; 525, 496, 413, and 381 observations for Italy, the UK, Japan, and Germany, Kim and In (2007) reveal scale-dependent findings. Apart from Japan, the other countries observe a negative correlation relationship between stock and bond yields. Besides, wavelet variance decomposition shows that stock returns are more volatile than bond yields in all countries, with only one exception for Japan. Dajcman (2015) reports the same results regarding the wavelet variance structure except for Portugal in ten European countries. The implication of this result for investors is that short-term traders should respond to every variation in asset returns to efficiently manage their portfolio risk. In addition, wavelet-based correlations between changes in bond yield and stock prices are mostly positive, except for Portugal, at all scales. It is also proved that the comovement between financial markets in Germany and Portugal exhibit both scale-dependent and time-varying phenomenon during the tested period. Tiwari (2012) examines the causal linkages between monthly stock prices and interest rates in India over the sample period between 1990-M01 and 2009-M03. Test findings of the cross-wavelet coherency approach show significant causality and both cyclical and anti-cyclical linkages over scales and periods. For example, a causality running from stock prices to interest rates is found at high frequencies corresponding to 1-4 years period. This finding implies that interest rates receive cyclical impact from stock prices. On the contrary, interest rates Granger-cause stock prices in 8-12 year horizon, indicating that stock prices receive cyclical impact from interest rates. Asgharian et al. (2015) investigate the factors that may have possible impacts on the correlation relationship between stocks and bonds in the long-term by conducting DCC-MIDAS models and wavelets. The authors reveal that the most factors including industrial production, inflation, short-term interest rates, trading volume, default spread, and producer and consumer confidence indices have significant power in the long run relation estimation. On the contrary, the effect of macro-finance variables on the long run (negative) correlation is found to be strong when the economy is weak. Ferrer et al. (2016) study the interdependence between share returns and movements in the long-term government bond yields by conducting wavelet coherency approach for several Eurozone countries. The main finding is that the interdependence considerably varies over time and frequencies and among countries. The strongest interdependence between markets is observed in the UK, while, on the other hand, markets in Portugal, Greece, and Ireland show the weakest interdependence over time. In addition, the strongest relationship is predominantly intensified at lower frequencies corresponding to one to two yearly

investment horizons. The empirical paper of Özer and Kamisli (2015), on the other hand, reveal significant spillover effects from equity returns to interest rates in the middle and lower frequencies in Turkey. More clearly, test findings report one-way causal linkages running from equity returns to macroeconomic factors including interest rates and exchange rates (in Dollar and Euro), however, the causality does not run in the inverse direction in the time domain. To uncover the hidden relationship that dispersed over frequencies, the authors implemented the Breitung and Candelon (2006) causality test and they find that the causality is concentrated on the medium – and long-term, driven mostly by trading activities of the foreign investors' pressure on stock market liquidity.

This paper reinvestigates the stock-bond nexus using 605 weekly observations of stock index prices consisting the aggregate (1), financials (6), services (7), industrials (8), technology (2), and investment trust (1) index and the 2-year benchmark rate of Turkey over a sample period covering April 1, 2005 and December 30, 2016. Why implement wavelet analysis instead of classical econometric tools? Because they have received a great deal of attention from researchers in recent years for their versatility and convenience of being able to provide simultaneously both frequency and time information of the data. Implementing wavelets allows researchers to unravel both the time and frequency behavior of the underlying time series at different time intervals, i.e. in the short, medium and long-term. Loosely speaking, it makes possible to get the details and overall picture that is to see both the trees and the forest. Indeed, the main advantage is to provide specific time intervals, such as "(2-4]", "(4-8]", or "(8<", days, weeks, years, etc., not uncertain time periods such as short – or long-term, as with the conventional methods. This is the distinguishing property of wavelets when particular frequency intervals are of interest to investors and/or policymakers, making them a convenient tool compared to other methods. Test results show weekly positive averages for all stock index returns and the negative average for bond yields over time. Wavelets variance analysis reveals that the higher scale the lower volatility, namely, the most of fluctuations in returns is explained by short-term, suggesting that short-term investors should react to every fluctuation in their asset returns. The variables that have the highest and lowest energy decompositions in the short run are "RXGIDA" and "RTR2YGB". Furthermore, the bond market is less volatile than almost all stock indices. On the other hand, test findings highlight, as expected and in common in literature, significantly negative linkages between stock and bonds up to the scale "d4" corresponding to 32 weeks. The most sensitive indices to bond yields are, not surprisingly, are "XU100", "XUMAL" and "XBANK" while "XSPOR", "XILTM" and "XBLSM" are less sensitive. Wavelet cross-correlation results show, in overall, significantly both positive and negative bidirectional causal linkages across wavelet scales, particularly concentrated on the higher scales. Changes in "RTR2YGB" at lower lags negatively and at higher lags positively lead both financials and non-financial indices up to the scale "d4" while the reverse lead-lag relationships also hold.

The remainder of the paper is laid as follows. Section 2 sheds the light on the relevant literature review. Section 3 describes the methodology, wavelets, we employed. Section 4 presents descriptive statistics for weekly variables and empirical results in terms of wavelet variance, wavelet correlations, and cross-correlations for Turkey case over the period between April 1, 2005 and December 30, 2016. Section 5 includes empirical and theoretical implications for investors and policymakers and recommendation on the future studies.

1. Literature Review

Of the studies that have investigated stock-bond relationship in developed countries, Saporoschenko (2002) study the sensitivity of returns of bank stocks to market returns, bond yields (short and long), change in interest rate spread, and exchange rate using weekly observations of 47 Japanese banks. Test findings show a significantly negative relationship between stock returns and shocks in long-term interest rates and strong interest rate sensitiveness for market returns and interest rate spread over time. Stock returns do not seem, however, to be very sensitive to the exchange rate movements. Connolly et al. (2005) report an adverse association between the future correlation of bond and stock returns and the uncertainty measures of VIX in the U.S. during the sample period between 1986 and 2000. Test results, in overall, provide a higher stock market uncertainty more benefit from bond-stock diversification. In a recent study, Kontonikas et al. (2013) find that stock prices are found to respond differently to unanticipated federal funds rate (FFR) in the U.S. The direction of respond from stock prices to unanticipated FFR, for example, is positive outside the crisis period; however, the relationship switches sign from positive to negative throughout the crisis period, indicating a signal of worsening economic conditions in the future and shifting towards safe-haven assets. In addition, Cenedese and Mallucci (2016) argue that the major factor driving international equity returns is the news related to future cash flows instead of discount rates while the main factor for international bond returns is found to be inflation rate in the US. Another remarkable result, on the other hand, is that exchange rate movements have a little effect on the volatility of bond and unanticipated equity returns over time. González et al. (2017) with a recent paper find negative associations between sectoral stock returns and changes in nominal and real interest rates in the U.S, with exceptions for "Diversified Metals and Mining" and "Integrated Oil and Gas" sectors that positively affected by movements in interest rates.

Using a sample dataset including 57 financial intermediaries and 47 industrial corporations, Oertmann et al. (2000) study the interest rate exposure of stock prices of firms operating in the UK, Germany, France, and Switzerland over the sample period between January 1982 and March 1995. Test findings show significantly negative sensitiveness for financial and significantly positive sensitiveness for nonfinancial firms. In addition, the most sensitive firms to global interest rate movements are the multinational companies operating in the UK and Germany. Accordingly, movements in both domestic and global interest rates could be accepted as driving forces of stock returns in the underlying markets. Bohl et al. (2003) ascertain positive but insignificant result between short-term interest rate and stock return using dataset both monthly and daily frequencies from Germany over the 1985-1998 period. The reason behind this finding is that the theoretical rationale between stock price and central bank reactions was not yet satisfactorily well-developed. Apergis and Eleftheriou (2002) report that stock prices followed inflation rate rather than T-bill interest rate yields since markets were characterized by declining inflation and interest rates in Greece during the sample period between 1988 and 1999. On the other hand, Joseph (2002) argues that industrial stock returns are adversely affected by T-bill rate yields rather than the exchange rate in the UK. According to test results, the electrical and engineering sectors were the two most negatively sensitive sectors while, on the other hand, the pharmaceutical sector was the only sector that positively influenced by movements in interest and exchange rates. Similar results are reported by Jareño (2008), who shows that industrial

returns of Spanish firms were significantly and adversely affected by movements in real interest rates over the sample period between 1993-02 and 2004-12. Ferrer and González (2010), on the other hand, report heterogeneous results for Spanish firms. Test findings show that the interest risk had considerable effects on firm returns at varying significance and magnitudes. Among industries, the food sector was the only sector that its returns were less affected by falling interest rates rather than rising interest rates. Conversely, the highly leveraged, regulated and financial sectors were the most interest rate sensitive among industries.

Employing the VAR model, Abugri (2008) seeks to investigate whether U.S. dollar-denominated market returns could be significantly explained by several macroeconomic variables in Brazil, Argentina, Mexico, and Chile. Being significantly explaining market returns in these markets provides investors useful information about portfolio diversification strategies, achieving better return-risk tradeoff, and improving their portfolio performances by concentrating on the varying significance of the risk factors. Korkeamäki (2011), on the other hand, presents significantly negative stock-bond correlation relationships for most of the EU countries earlier than 1999, which disappeared after 1998, and suggests that interest risk was priced for global investors in the post-euro era. Test findings of the paper by Jammazi et al. (2015) observe that the stock-bond comovement pattern has changed noticeably over time for most countries under study. More clearly, positive relationships are reported for almost all developed countries due to falling inflation rates and strengthening economic prospects during the 1990s. From the early 2000s, however, the markets exhibited adverse relationships until 2009 because the Eurozone sovereign debt crisis changed the stock-bond correlation in Greece, Portugal, Spain, Belgium, and Ireland. The author says that this swing represents the flight-to-quality in those countries.

Negative relationship between stock and bond is maintained by Maysami and Koh (2000) for Singapore, Liu and Shrestha (2008) for China, Jawaid and Ul Haq (2012) and Ismail et al. (2016) for Pakistan, Udegbunam and Oaikhenan (2012) for Nigeria, Barakat et al. (2015) for Egypt and Tunisia, Liu and Chen (2016) for Taiwan. Maysami and Koh (2000) find that stock market is significantly positive related to short-term interest rates but negative associated with long-term interest rates over a sample period between January 1988 and January 1995 in Singapore. This result shows that the long-term rates are a better proxy than short-term interest rates for valuing assets. Liu and Shrestha (2008) document long-run linkages between a set of variables and stock prices using 120 monthly observations over time in the Chinese markets. Finding a significantly negative relationship between interest, inflation and exchange rates with stock prices shows that the stock market could offer better long-term returns and diversification opportunities to investors. Furthermore, Jawaid and Ul Haq (2012) report significantly negative and positive linkages between interest rate and exchange rate with banking share prices in the long and short run, respectively, while, on the other hand, a unidirectional causality between stock and bonds, suggesting that both variables were reasonable indicators for investment decisions in the banking index in Pakistan. However, Ismail et al. (2016) find out a positive but insignificant result from interest rates, money supply, and exchange rate to share returns in Pakistan. Udegbunam and Oaikhenan (2012) reveal significantly negative effects of net interest rate movements on stock prices in Nigeria and they conclude this finding as evidence in favor of the existence of a non-linear relationship between stock prices and interest rate risk regarding duration and

convexity hypothesis. Barakat et al. (2015), on the other hand, find significantly negative long-run relationship between interest rate and stock prices in Egypt but insignificant result in Tunisia. A noteworthy finding of this study is, however, bidirectional causality in Tunisia and unidirectional causal relationship in Egypt. Test result suggests that stock market does not have a predictive power on changes in interest rate in Egypt. Besides, Liu and Chen (2016) document that the lagged values of interest rates had significant effects on the covariance between stock price and interest rate while stock market volatility had significantly positive impacts on interest rates in Taiwan for the sample period between January 1985 and March 2009.

In addition to the papers investigating the bond-stock relationship in developed and developing countries, we also present an illustrative list of studies that concentrate on Turkish markets. This set includes research papers of Erdem et al. (2005) who examine the price volatility spillovers, Duran et al. (2010) who study the effect of monetary policy decisions, Sayilgan and Süslü (2011) and Kasman et al. (2011) who research the effects of macroeconomic factors, Sensoy and Sobaci (2014) ,Uyar et al. (2016) and Sancar et al. (2017). For example, Erdem et al. (2005) contend that the length of volatility persistence of stock indices is shorter compared to interest rate, exchange rate, money supply, industrial production, and inflation. There is significantly negative evidence for volatility spillovers from interest rate to "XUHIZ" index, inflation to "XU100" and "XUSIN" indices, and money supply to "XUMAL" index. In addition, the authors find significantly positive volatility spillovers from interest rate to "XU100", "XUMAL", and "XUSIN", the exchange rate to "XU100" and "XUSIN", and from inflation to "XUHIZ" indices. By conducting event study and GMM approaches over the period 2005 to 2009 for Turkey, Duran et al. (2010) argue that monetary policy decisions have varying significantly negative impacts on stock indices of "XU100", "XUTUM", "XU030", "XUMAL", "XUSIN", "XTCRT", "XUHIZ", and "XBLSM" due to different balance sheet compositions. On the other hand, Sayilgan and Süslü (2011) show significant effects from inflation, exchange rate and S&P500 index and statistically insignificant, however, for interest rates, oil price, real economic activity, and money supply to stock returns in eleven countries including Turkey, Argentina, Indonesia, Chile, Hungary, Malaysia, Mexico, Poland, Russia, Jordan and Brazil. Kasman et al. (2011) report a significantly negative evidence of interest and exchange rate effects on the conditional daily share returns of "XBANK" index and 13 individual commercial bank stocks during the period under investigation. Test results suggest investors to follow the movements in interest rate and exchange rate more closely for adapting their portfolio compositions because both have explicative power on the conditional daily stock returns. In their empirical paper, Sensoy and Sobaci (2014) document time-dependent association between stock and bond markets by using a dynamic conditional correlation approach. Because this relationship is only valid in the short term the authors claim that there is no need to react to prevent a long run contagion between two markets. On the other hand, Uyar et al. (2016) find that stock indices of "XUMAL" and "XBANK" are found to be more sensitive to adverse effects from interest movements during tested period covering 2006-01-02 and 2015-01-30, suggesting investors to adjust their portfolio compositions at periods of rising or falling in the stock markets. By using daily observations, Ekinci et al. (2016) discover that there are no significant effects from the weighted average cost of the CBRT funding to "XU100" over the February 21, 2013–July 26, 2016 period. Sancar et al. (2017), however, find that interbank interest rate is the only factor among a set of variables including

industrial production index, M1 money supply, exchange rate, consumer price index that not significantly related to stock prices in the long run.

It is evident from the paper results that they are totally focused on the contemporaneous linkage between stock returns and bond yields. In order to determine the time-scale based relationship, however, there should be versatile methods such as frequency causality tests, Fourier or wavelet analysis. A noteworthy series of research studies focused on the stock-bond relationship using wavelet approach are reported by Andrieş et al. (2014) for India, Dimic et al. (2016) for the U.S. and ten emerging markets, and Bayraci et al. (2018) for Turkey. By implementing cross-wavelet power, cross-wavelet coherency, and phase difference approaches, Andrieş et al. (2014) document that association among exchange rate, interest rate, and stock prices is significant and the direction and strength depends on the frequency bands. Furthermore, test findings show that stock prices follow the changes in interest rate and exchange rate in India. However, the stock market causes exchange rate towards the end of 2009. The interest rate and stock market relationship is clearer after 2006 and the authors argue that stock prices may be may effectively affected by monetary authorities for specific frequency bands corresponding to 3 months and 3 years. Dimic et al. (2016), on the other side, find out that ten emerging markets –Brazil, Argentina, Bulgaria, Mexico, Russia, Turkey, Venezuela, the Philippines, Colombia, and Peru– except Venezuela had significantly positive, while the U.S. had significantly negative unconditional stock-bond correlation relationship over the sample period spanning from January 2001 to December 2013. Moreover, test findings of wavelet coherence approach illustrate that bond-stock correlation did change significantly across frequency bands, i.e. the sing and magnitude of short-term correlation changed quickly from positive to negative eras corresponding to the crisis period, implying the existence of "flight-to-quality" phenomenon in the short run (high-frequency). These findings suggest that investors did adjust their asset compositions in favor of debt market instruments during crises period because of hedging incentives. The long-term based test findings, on the other hand, show that stock-bond correlation relationship is positive during the entire period in all emerging markets except for Venezuela, indicating evidence in favor of flight-from-quality phenomenon at the lower frequency bands. Moreover, the stock-bond correlation is found to be most sensitive to the monetary policy decisions in the short-run and to uncertainty in stock markets and inflation in the long run. By conducting wavelet coherence approach, Bayraci et al. (2018) investigate the dynamic stock-bond correlation relationship in G-7 countries. The findings of paper provide evidence in favor of frequency-dependent positive relationship between markets. At high-frequency bands, the co-movement is weak while, on the other hand, it strengthens at lower frequency, i.e. in the long-term investment horizon, corresponding to 128 and 512 days, association becomes stronger. Furthermore, wavelet analysis also shows lead-lag relationships between two variables. At the time of global financial crisis, for example, stock returns lead bond yields in the U.K., Germany and France at the highest-frequency bands corresponding to 2-4 days. Conversely, bond returns causes stock returns at time horizon of 4-16 days and the reverse also holds as scales 2-4 days in Italy. The positive and strong relationship intensified at time scales of 64-512 days between stock and bond markets provide investors a hedging opportunity in G7 countries. The authors argue that these results support the heterogeneous market hypothesis introduced by Müller et al. (1993), namely, long-term investors are probably to follow macroeconomic fundamentals while short-term investors are expected to follow trends and respond to bad and good events in financial markets.

Therefore, it is likely to see a time-varying stock-bond connection across frequency bands. On the other side, test findings of rolling wavelet correlations show that correlation association is very volatile and significantly increases during in the bearish markets because investors shift their funds from stocks to bonds when their sentiments and risk preferences change.

2. Methodology

Following previous literature, the stock-bond relationship can be measured within the framework of time and frequency domains. Having received a great deal of attention, wavelets are very efficient and appealing tool when a particular time interval is of interest to be elucidated. We begin by presenting a brief review of the Fourier transform theories. Said that, a general discussion on the fundamentals of wavelet analysis will be provided, i.e. the discrete wavelet transforms ("DWT"), and the maximal overlap discrete wavelet transforms ("MODWT"). After that we go on delving into the details of wavelet variance, covariance, correlation, and cross-correlation estimations.

Figure 1. Fourier vs. Wavelet Transforms
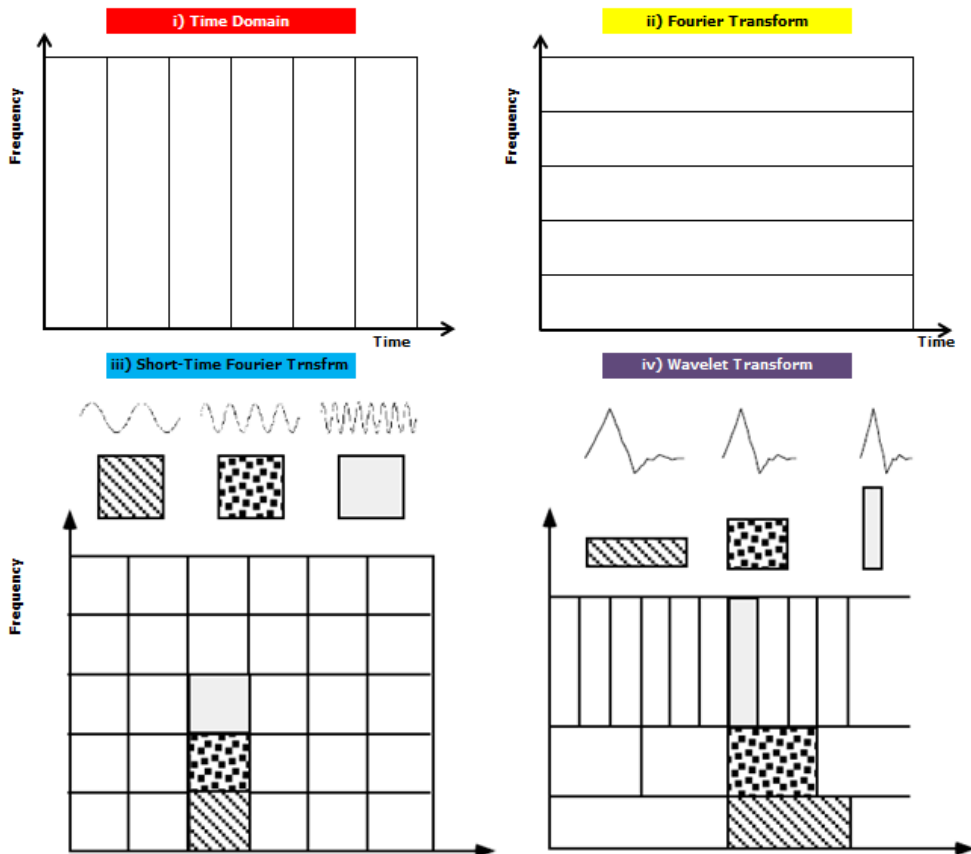
Source: Gencay et al., 2002, s.98.

2.1. Fourier vs. Wavelets

Mallat (1989, s.689) states that the Fourier analysis was introduced by the French mathematician J.B. Joseph Fourier in the beginning of the 19th century. The main idea is that an arbitrary 2π periodic function of frequency can be represented as an infinite sum of the sinusoids, i.e. dilated sine and cosines. The Fourier representation of any deterministic function $f \in L^2 [-\pi,\pi]$ is given by (In and Kim, 2012, s.2)

$$f(x) = \frac{1}{2}\lambda_0 + \sum_{j=1}^{J}(\lambda_j \cos(jx) + \beta_j \sin(jx)) \tag{1}$$

where $\{\lambda\_0, \lambda\_1, \beta\_j, \ldots\}$ coefficients represents a complex sequences. As contended by Gencay et al. (2002, s.97), the function in Equation (1) is an example of the discretely sampled process of an $f(x)$ function generated by a linear combination of the basic trigonometric sinusoids and it is a decomposition on frequency-by-frequency basis of the discrete Fourier transforms. These basis functions, sine and cosines, are, however, are very appealing when the underlying data is stationary. Indeed, the periodic nature of a signal with two sinusoids having different size and amplitude is succinctly captured by only a few Fourier coefficients. Ramsey (2014, s.12) assert that Fourier series are capable of fitting global variation whereas they respond to local variations only at very high frequencies, therefore, Fourier series need a considerably more coefficients for a given level of approximation.

The Fourier transform is an alternative representation of the original data and it basically converts this data from one domain (time or frequency) to another (frequency or time) domain (Gencay et al., 2002, s.99). It summarizes frequency information but cannot preserve time information since its basis functions have infinite support. Given that the sinusoids are only localized in frequency, the output is a global picture of the data. Figure 1 depicts both the time (i) and frequency representation (ii) of data through the time-frequency plane. Looking at the representation in the time domain, we observe complete time resolution but no frequency resolution. Conversely, we have complete frequency resolution but no resolution in the case of the Fourier transforms.

On the left in Figure 1 we graph a time-frequency representation through a modified time-dependent version of the Fourier transforms. This new version is called as short-time Fourier and introduced by D. Gabor in 1946 to overcome the main disadvantage of the Fourier transform that is stationarity requirement. As noted by Gallegati (2008, s.3063), this method uses a fixed window function with respect to frequency and transforms this windowed data by the Fourier transform to obtain a sort of compromise between frequency and time. The main assumption is the stationarity of the partitioned small sections over the duration of the window function. The output is a decomposition of two parameters, time and frequency shift, namely, a time-frequency representation. Note that the accuracy of the transformation is attributed to the size of the window with respect to frequency and the effect of the window function is to localize the data in time (In and Kim, 2012, s.4). Actually

the choice of the length of the window depends on the trade-off between the desired frequency resolution and once a decision made for the window function it is not allowed to change it for other frequencies. It is the main drawback because it cannot resolve events if they happen to appear within the width of the window. The major reason behind this result proceeds from the Heisenberg uncertainty principle, which states that one cannot obtain both a good resolution in time and frequency simultaneously. Evidently, both the frequency and time resolutions of the time series are the same for times and frequencies, respectively.

To overcome the drawbacks of the STFT approach, a different method called as wavelet transform was introduced by researchers. The wavelet term mentioned first by Grossman and Morlet in 1984 literally means small or short waves that grows and dies out in the short-time because of having finite length and oscillatory behavior (Soman et al., 2010, s.31). In order to capture features that are local in both frequency and time, the wavelet transform uses a basic function called mother wavelet and its scaled and translated versions. Equivalently speaking, the mother wavelet is squeezed or dilated to capture the frequency information whereas it is shifted (translated) on the time axis to capture the time information from the underlying data. The outcome is described as continuous wavelet transform if the transform is computed for all data locations and wavelet scales at continues steps or discrete wavelet transform in the case of a process at discrete steps. Since financial time series are observed at regular intervals, in this paper we merely concentrate on the discrete wavelet transform.

Indeed, it is, as noted by Gencay et al., (2002, s.99), one of the most important properties to attain the frequency content of a process as a function of time, namely to present a time-scale (time-frequency) representation which its success depends on the local matching of the basis function with the data. Since wavelets have good frequency and time localization properties their transform is long in (time) frequency when capturing high – (low) frequency events, therefore, they display good (poor) time resolution but poor (good) frequency resolution. It can be said that the wavelet transform intelligently adapts itself to capture frequency and time behaviors of the data across a wide range of frequencies. It is the main reason that wavelets are accepted as an ideal tool for studying transient or nonstationary data. As depicted in Figure 1, wavelets use long (short) windows at low (high) frequencies, therefore, provide simultaneous frequency and time resolutions that vary in the frequency-time plane by two main parameters: time and scale (frequency).

For wavelet analysis, as dictated by Ramsey (2014, s.12), there are two basic wavelet functions called as mother $\psi(t)$ and father wavelet $\phi(t)$. The father wavelet integrates to 1 and reconstructs the smooth, trend (low-frequency) part of the data, while the mother wavelet represents the detailed (high-frequency) parts, i.e. can capture all deviations from the trend and integrates to 0. The approximating wavelet functions generated from mother and father wavelets through scaling and translation is given by

$$\psi_{J,k}(t) = 2^{-\frac{J}{2}}\psi\left(\frac{t - 2^J k}{2^J}\right) \qquad \& \qquad \phi_{J,k}(t) = 2^{-\frac{J}{2}}\phi\left(\frac{t - 2^J k}{2^J}\right) \tag{2}$$

where J and k index the scales and the translation, respectively. Hence, $2^J k=a$ and $2^J=b$ and are the dilation and translation parameters. Crowley (2007, s.210) reports that b controls the length of the window and a is a measure of the location. In addition, $1/\sqrt{b}$ parameter guarantees that the norm of $\psi(.)$ is equivalent to one and the energy is intensified in a neighborhood of the translation parameter, a, with size proportional to the scaling parameter, b. Gencay et al. (2002, s.144) state that if the scale parameter of wavelet transform decreases (increases), then the wavelet basis is shifted toward lower (higher) frequencies, the time support declines (increases) and the number of frequencies captures increases (decreases). After defining the approximating wavelet functions, it is easy to build up any time series $x(t)$ as a sequence of projections onto mother and father wavelets that indexed by both J and k as $s_{J,k}=\int \phi_{J,k}(t)f(t)$ and $d_{J,k}=\int \psi_{J,k}(t)f(t)$ where j=1,...,J such that J is the maximum scale sustainable with the data to hand (Ramsey, 2014, s.12). Besides, the smooth coefficients $s_{J,k}$ represent the smooth behavior of the data whereas the detail coefficients $d_{J,k}$ correspond to the progressively finer scale deviations from the smooth behavior. The first (second) coefficients capture the low (higher) frequency oscillations. We can use the smooth and detail coefficients to obtain the smooth $S_{J,k}$ and detail signals $D_{J,k}$ of the data in hand, as follows:

$$S_{J,k} = \sum_k S_{J,k}\phi_{J,k}(t) \qquad \& \qquad D_{J,k} = \sum_k d_{J,k}\psi_{J,k}(t) \tag{3}$$

Ramsey (2014, s.10) assert that wavelets can be generated by the combination of two filter members: the low g_l and high pass h_l filters. The low filter g_l produces a moving average while the linear time-invariant operator, the high filter h_l, produces moving differences. They are corresponding to father and mother wavelet filters, respectively. The filter coefficients of a finite length discrete wavelet ("DWT") filter must have zero mean, that is integrate to zero, $\sum_{l=0}^{L-1} h_l = 0$, unit energy, $\sum_{l=0}^{L-1} h_l^2 = 1$, and be orthogonal to their even shifts, $\sum_{l=0}^{L-1} h_l h_{l+2n} = 0$, for all non-zero integers.

Without giving the details of the "DWT", we restrict our study to a non-decimated version of the "DWT", that is the maximal overlap discrete wavelet transform, the "MODWT". It is natural to ask why we prefer the "MODWT" instead of the "DWT". Whitcher et al. (2000, s.14944) report that the "MODWT" gives up orthogonality property of the "DWT" (through not subsampling) to gain other features that "DWT" does not have. Percival and Walden (2000, s.159-160) state that the "MODWT" has some critical advantages over the "DWT". The first advantage is that the former method can handle any sample size N, while the scale level of the latter one is restricted to a positive integer multiple of 2^{J0}. Equivalently speaking, whether N is dyadic or not is not important for the "MODWT". Besides, both methods can be used to form a multiresolution analysis, however, only the detail and smooth coefficients of a "MODWT MRA" are associated with zero phase filters, namely, events that feature in the original data may be accurately lined up features in the "MRA". On the other hand, the "MODWT" is invariant to circularly shifting the time series under investigation; therefore, the coefficients of the "MODWT" do not change if they are shifted by an integer unit, which does not hold for the "DWT". Even though it is true for both methods, the "MODWT" coefficients produce a more asymptotically efficient wavelet variance estimator than the "DWT", and provide increased resolution at coarser levels since it oversamples the series.

2.1.1. Multiresolution Decomposition

A multiresolution analysis is a wavelet transforms process that gives a chance to obtain a scale-invariant interpretation of the underlying series (Mallat, 1989, s.674). In order to obtain a narrower (wider) scene, the camera must be got by a resolution step Ω times further (closer) to the scene. Therefore, it produces both the details and overall picture of the signal/data as if a camera zooms in or out on scaling function. Daubechies (1992, s.3) demonstrate that the transformation process is performed through the pyramid (cascade) algorithm. The multiresolution approximation building up an underlying $X(t)$ variable from the coarsest scale downwards up to scale J can be written as follows (Ramsey, 2014, s.12):

$$X(t) = S_J(t) + \sum_{j=1}^{J} D_j(t) = D_1(t) + \cdots + D_{J-2}(t) + D_{J-1}(t) + D_J(t) + S_J(t)$$

(4)

where the $S_J(t)$ parameter includes the smooth component and the $D_J(t)$ parameters include the detail components at an increasingly finer resolution level. As noted by Gallegati et al., (2017, s.8) the latter component is the degree of difference of the observations of the series at each scale and it represents the scale deviation from the smooth process, while, on the other hand, the former component provides the smooth long-term features of the underlying data. The additive decomposition feature enables to easily reconstruct the original series, $X(t)$, by summing up the detail and smooth components. For example, the smooth parameter, S_2, at scale $j=2$ is equal to $S_2=S_3+d_3$ and $S_2=S_1-d_2$.

2.1.2. Wavelet Variance, Covariance, and Correlations by Scale

By using non-boundary wavelet coefficients generated by "MODWT" function, we can obtain wavelet tools such as wavelet variances, covariances, correlations and cross-correlations to unravel both the time and frequency behavior of the underlying time series. A wavelet variance of time series, for example, as noted by Percival and Walden (2000, s.296), can be defined as a practical concept for both stationary process and nonstationary process with stationary backward differences. As demonstrated by Lindsay et al. (1996, s.778), decomposing a sample variance into a scale-by-scale basis, leads to both the notion of the scale-dependent estimation and determination of the locations of the events contributing to the total sample variance at each time horizon. The wavelet variance, according to Percival (1995, s.621), is a particular part of total sample variance, where the total variance comprises of several scale-based variance components.

In wavelet literature, the wavelet variance is accepted as an energy decomposition of time series in the frequency domain because of zero-mean property of wavelet coefficients. Since the "MODWT" wavelet transformation has an energy preserving property, the sum of the energies of the wavelet and scaling coefficients will be equal to the total energy of the original time series. With a condition of $j=1,...,J$, the energy decomposition of wavelet analysis is given by (Gallegati and Ramsey, 2013, s.66)

$$\|X\|^2 = \sum_{j=1}^{J} \|\tilde{w}_j\|^2 + \|\tilde{v}_j\|^2 \tag{5}$$

where $\tilde{w}_j$ and $\tilde{v}_j$ signifies wavelet and scaling coefficients derived from wavelet transform process, respectively. Evidently, Equation (5) allow one to partition the sample variance by resolution level and identify which scale level contribute considerably more variation to the overall variability relative to other scales. Given a stationary or nonstationary stochastic process, as $X(t)$, its time-varying, i.e. the time-dependent, wavelet variance decomposition at scale j is as follows (Crowley, 2007)

$$\sigma_{X,t}^2(\lambda_j) = \frac{1}{2\lambda_j} \mathrm{var}\left(\omega_{j,t}\right) = \mathrm{var}\{\bar{W}_{j,t}\} \tag{6}$$

where λ_j and $w_{j,t}$ denote the j th scale level and the j th scale level coefficients, respectively. Some difficulties arise when one intends to obtain time-independent wavelet variance and calculate wavelet variance for each scale and account for when decimation takes place. In the case of a finite and time-dependent wavelet variance, on the contrary, the equation above can be rewritten as Percival and Walden (2000, s.296)

$$\sigma_X^2(\lambda_j) = \mathrm{var}\{\bar{W}_{j,t}\} \tag{7}$$

where the statistical properties of $X(t)$ at each scale are invariant over time. Besides, a time-independent wavelet variance can be defined for stationary and non-stationary process with both stationary (i) dth order differences and (ii) local stationarity. The sufficient condition for being time-independent wavelet variance for (i), however, is to have a large enough the length of wavelet filter, L, namely, the filter size must be at least equal to the size of the differencing order, d, that is $L \geq d$. An unbiased estimator of the wavelet variance at scale λ_j obtained by the "MODWT" function is

$$\tilde{\sigma}_{X,j}^2(\lambda_j) = \frac{1}{\tilde{N}_j} \sum_{t=L_j-1}^{N-1} \tilde{\omega}_{j,t}^2 \tag{8}$$

where $\tilde{N}_j[= N - L_j + 1]$ and $L_j[=(L-1)*(2^j-1)+1]$ represent the number of coefficients uninfluenced by the boundary conditions for each scale λ_j and the wavelet filter length or the number of coefficients that affected by boundary condition, respectively. One may notice that only non-boundary wavelet coefficients are used for wavelet variance estimation since the "MODWT" employs circular convolution, therefore, using the coefficients generated by both beginning and ending series would imply biasedness. As noted by Masset (2008, s.), this problem arises in two situations. The first case concerns only the "DWT" because of dyadic length for time series. To overcome, one must remove or add some observations so that $N=2^j$. The second case, however, concerns both the "MODWT" and the "DWT". During decomposition, the wavelet filter, L, must be applied on all observations, from the beginning ($t=1$) to end of the series (N). The reason behind the problem is that the convolution operator requires at least L-1 observations before t during process. One solution is to add sufficient observations with zeros by zero-padding technique. Similarly, one can also complete the

series by the "reflection" or "periodic" techniques. By the "reflection" technique including two methods: symmetric and anti-symmetric reflection, the series is mirrored or extended to length $2N$ that is $x_0, \dots, x_{N-2}, x_{N-1}, x_{N-1}, x_{N-2}, \dots, x_0$. One may notice that all coefficients are duplicated once, therefore, reflecting time series does not change the sample mean nor the sample variance (Gencay et al., 2002, s.144). Conversely, the "periodic" or "circular" technique presumes that N is periodic series and takes the observations at the beginning of the other end of the series. In and Kim (2012, s.28) demonstrate that this method is more preferable since one can straightforwardly implement and its resulting coefficients are independent with identical variances. After deciding wavelet filter length, we are left by the number of non-boundary wavelet coefficients equal to N-L_j. Notice that longer the width of the wavelet filter used less the number of coefficients left for each stage of the wavelet transform, 2^{j-1}, namely, as scale level increases the number of useful coefficients decreases. The third method to handle the boundary condition is to impose the brick wall condition and simply remove the affected coefficients from the series.

It is easy to derive the wavelet covariances between two time series of interest after their variances are calculated. Whitcher et al. (2000, s.14945) developed a framework for wavelet covariance and correlation estimations along with their confidence intervals. An unbiased estimator of the wavelet covariance at scale λ_j and zero lag between two stochastic processes, X_t and Y_t, whose their dth order backward differences are stationary Gaussian process after implementing brick wall condition using "MODWT" can be given as

$$\gamma_{X,Y}(\lambda_i) = \frac{1}{\tilde{N}_j} \sum_{t=L_j-1}^{N-1} \widetilde{W}_{X,j,t} \widetilde{W}_{Y,j,t} \tag{9}$$

where $\tilde{N}_j = N - L_j + 1$. As demonstrated by Lindsay et al. (1996, s.778), the "MODWT" estimator $\gamma_{X,Y}(\lambda i)$ is asymptotically normally distributed with mean and large sample variance.

In and Kim (2012, s.34) remark the important fact that covariance measure does not take into consideration the strength of the association, therefore, it is required to turn our attention to the wavelet correlation. Given the wavelet variance estimator in Equation (8) and covariance estimator in Equation (9), the wavelet correlation estimator between two stochastic processes, X_t and Y_t, for scale λ_j based on the unbiased "MODWT" coefficients is given by

$$\hat{\rho}_{X,Y}(\lambda_i) = \frac{\gamma_{X,Y}(\lambda_i)}{\sigma_X(\lambda_j) * \sigma_Y(\lambda_j)} \tag{10}$$

where $\gamma_{X,Y}(\lambda i)$ is the covariance and $\sigma_X(\lambda_j)$ and $\sigma_Y(\lambda_j)$ are the square root of the wavelet variance of X and Y, respectively. Gencay et al. (2002, s.258) state that the correlation is $|\hat{\rho}_{X,Y}(\lambda_i)| < 1$ as with the usual standard coefficient. Notably, the wavelet correlation corresponds to its Fourier equivalent, the complex coherency. Besides, the confidence intervals for correlation estimations that corrected by a non-linear transformation, $h(\hat{\rho})$, for each wavelet scale can be expressed as

Table 1: Descriptive Statistics of Return Series

Variables	Mean	SD	Min	Max	Skewness	Kurtosis	JB		n
DL_TR2YGB	-0.0010	0.0339	-0.1361	0.1953	0.7012	6.9793	447.99	***	604
DL_XU100	0.0018	0.0380	-0.1927	0.1576	-0.4538	5.1638	138.56	***	604
DL_XUMAL	0.0017	0.0447	-0.2169	0.2035	-0.3100	5.1215	122.94	***	604
DL_XBANK	0.0017	0.0487	-0.2059	0.2151	-0.1724	4.6049	67.81	***	604
DL_XFINK	0.0021	0.0463	-0.3598	0.2466	-0.7402	12.3350	2248.23	***	604
DL_XGMYO	0.0008	0.0382	-0.1955	0.1109	-0.9653	5.8977	305.10	***	604
DL_XHOLD	0.0015	0.0420	-0.2450	0.1967	-0.5723	6.4615	334.52	***	604
DL_XSGRT	0.0025	0.0438	-0.2885	0.1648	-1.0315	8.9631	1001.97	***	604
DL_XUSIN	0.0022	0.0328	-0.2012	0.1182	-1.0299	6.8019	470.54	***	604
DL_XGIDA	0.0022	0.0375	-0.1720	0.1201	-0.3345	4.9350	105.49	***	604
DL_XKAGT	0.0010	0.0388	-0.2297	0.1343	-0.5219	5.8779	235.86	***	604
DL_XKMYA	0.0024	0.0385	-0.1772	0.1616	-0.4629	5.1143	134.07	***	604
DL_XMANA	0.0028	0.0471	-0.2442	0.2092	-0.6311	6.0115	268.34	***	604
DL_XMESY	0.0026	0.0398	-0.2664	0.1462	-1.0675	7.8306	701.96	***	604
DL_XTAST	0.0016	0.0316	-0.1592	0.1128	-0.7356	4.9985	154.99	***	604
DL_XTEKS	0.0020	0.0360	-0.2255	0.1102	-0.9645	6.8707	470.69	***	604
DL_XUHIZ	0.0021	0.0305	-0.1310	0.1573	-0.3166	4.9074	101.64	***	604
DL_XELKT	0.0004	0.0491	-0.3515	0.3541	-0.3333	12.2637	2170.90	***	604
DL_XILTM	0.0008	0.0397	-0.1422	0.1426	-0.1267	3.9193	22.88	***	604
DL_XSPOR	0.0014	0.0509	-0.4580	0.2246	-1.0546	16.3996	4630.60	***	604
DL_XTCRT	0.0036	0.0369	-0.2351	0.2793	-0.0189	10.9406	1586.87	***	604
DL_XTRZM	0.0003	0.0480	-0.2237	0.1844	-0.4723	5.4039	167.89	***	604
DL_XULAS	0.0028	0.0524	-0.2973	0.2029	-0.4437	5.6122	191.53	***	604
DL_XUTEK	0.0032	0.0400	-0.1958	0.1345	-0.6553	5.0615	150.17	***	604
DL_XBLSM	0.0020	0.0421	-0.1875	0.1786	-0.4018	5.9064	228.83	***	604
DL_XYORT	0.0007	0.0317	-0.1923	0.0950	-1.1748	7.7277	701.44	***	604

*,**, and *** indicate 10%, 5%, and 1% significance level, respectively.

$$h(\hat{\rho}) = \frac{1}{2} log \left(\frac{1 + \tilde{\rho}}{1 - \hat{\rho}} \right) = tanh^{-1}(\hat{\rho}) \tag{11}$$

$$tanh \left\{ h\left[\hat{\rho}_{XY}(\lambda_j)\right] \pm \frac{\Phi^{-1}(1-p)}{\sqrt{\hat{N}_j - 3}} \right\} \tag{12}$$

where $h(\hat{\rho})$ denotes Fisher's z transform and the estimated correlation coefficient $\hat{\rho}$ is based on N independent samples. Additionally, $\sqrt{N-3}[h(\hat{\rho}) - h(\rho)]$ is approximately distributed as a Gaussian with unit variance and zero-mean, i.e. has a $N(0,1)$ distribution. The $\sqrt{N-3}$ factor is used for a better approximation of the distribution. Notably, the quantity $\hat{N}_j$ is the number of wavelet coefficients generated by "DWT" transformation because the assumption of uncorrelated observations of Fisher's z transform works if we believe there are no any non-stationary features or systematic trends in

the wavelet coefficients at each wavelet level. Applying the transformation tan*h* maps the confidence interval back to between [-1,1] to generate an approximate 100(1-2*p*)% confidence interval based on "DWT" coefficients since they produce more reasonable confidence intervals. Similarly, the wavelet cross-correlation coefficients for each wavelet scale λ_j and lag τ based on the "MODWT" transformation is given by

$$\hat{\rho}_{\tau,X,Y}(\lambda_i) = \frac{\gamma_{\tau,X,Y}(\lambda_i)}{\sigma_{\tau,X}(\lambda_j) * \sigma_{\tau,Y}(\lambda_j)} \qquad (13)$$

Just as the standard unconditional cross-correlation, $\hat{\rho}_{\tau,X,Y}(\lambda_i)$ can be used to measure lead/lag relationships at each scale between two time series. At zero lag, $\tau = 0$, the cross-correlation is equal to simple wavelet correlation coefficient.

3. Empirical Results

In order to examine the nexus between stock returns and changes in interest rates, we used weekly (end-of-week) observations of Turkey two-year government bond yields and stock market indices –the aggregate (1), financials (6), services (7), industrials (8), technology (2), and investment trust (1) indices– obtained from the CBRT Bloomberg Terminal and the Borsa Istanbul A.Ş database, respectively. The weekly sample period is between April 1, 2005 and December 30, 2016, totaling 605 price observations. Weekly continuously compounded return series is calculated using the change in the natural log prices, i.e. $r_t = \log(P_t/P_{t-1})$ where *Pt* and P_{t-1} are the current and previous closing prices. Table 1 reports the results of the basic descriptive statistics for the weekly returns.
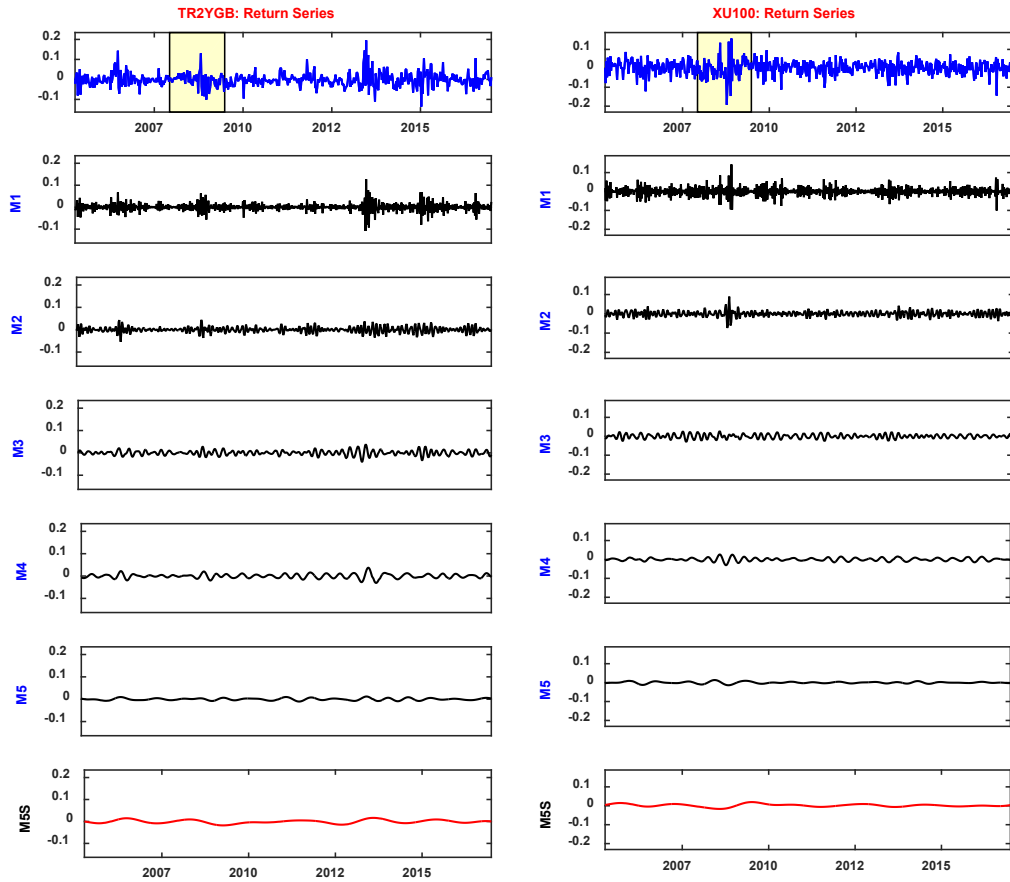
Table 2: Unit Root Tests Results

Variable	Level				Return					
	ADF	KPSS		PP	ADF		KPSS	PP	
LTR2YGB	-1.765	0.353	***	-2.014	-13.99	***	0.057	-21.551	***
LXU100	-2.822	0.133	*	-2.991	-15.932	***	0.042	-25.225	***
LXUMAL	-2.896	0.134	*	-3.05	-15.941	***	0.042	-24.694	***
LXBANK	-2.815	0.195	**	-2.964	-16.287	***	0.04	-25.548	***
LXFINK	-2.275	0.133	*	-2.494	-14.744	***	0.052	-23.086	***
LXGMYO	-2.344	0.212	**	-2.638	-14.803	***	0.044	-23.272	***
LXHOLD	-2.604	0.296	***	-2.687	-16.194	***	0.045	-22.956	***
LXSGRT	-2.738	0.232	***	-2.945	-14.349	***	0.051	-22.229	***
LXUSIN	-2.529	0.303	***	-2.756	-16.056	***	0.042	-26.047	***
LXGIDA	-1.477	0.321	***	-1.53	-18.617	***	0.071	-29.935	***
LXKAGT	-2.367	0.202	**	-2.622	-15.95	***	0.045	-22.861	***
LXKMYA	-2.27	0.327	***	-2.539	-17.378	***	0.04	-26.889	***
LXMANA	-2.299	0.308	***	-2.683	-16.068	***	0.032	-25.286	***
LXMESY	-1.661	0.649	***	-1.598	-14.911	***	0.046	-23.753	***

LXTAST	-2.448	0.119		-2.697		-14.883	***	0.064	-22.831	***
LXTEKS	-2.342	0.243	***	-2.479		-15.347	***	0.061	-24.106	***
LXUHIZ	-2.543	0.136	*	-2.499		-16.98	***	0.042	-26.57	***
LXELKT	-2.014	0.401	***	-2.324		-17.34	***	0.037	-25.986	***
LXILTM	-2.988	0.252	***	-3.151	*	-18.313	***	0.028	-28.636	***
LXSPOR	-2.139	0.493	***	-2.006		-17.232	***	0.081	-22.147	***
LXTCRT	-2.51	0.288	***	-2.65		-17.075	***	0.046	-27.996	***
LXTRZM	-2.818	0.103		-3.191	*	-15.208	***	0.065	-24.294	***
LXULAS	-1.707	0.245	***	-1.744		-16.463	***	0.087	-23.955	***
LXUTEK	-0.218	0.554	***	-0.502		-14.934	***	0.058	-24.08	***
LXBLSM	-1.625	0.3	***	-1.907		-14.964	***	0.057	-23.376	***
LXYORT	-2.136	0.265	***	-2.317		-16.966	***	0.059	-23.991	***

*,**, and *** indicate 10%, 5%, and 1% significance level, respectively.

Evidently, all weekly returns are close to zero; the average weekly stock returns are positive and the changes in interest rates are negative, indicating a good and poor performance for the stock returns and government bond yields over time. Notable, the minimum and maximum weekly returns are observed for the same stock indices of "DL_XSPOR", "DL_XFINK", and "DL_XELKT". As expected, the volatility of stock market indices is almost higher than bond markets, namely, the standard deviation of "DL_TR2YGB" (3.39%) is the fifth lowest rank after "DL_XUSIN", "DL_XYORT", "DL_XTAST", and "DL_XUHIZ" over the whole sample period. The highest volatile stock indices are, however, "DL_XULAS" (5.24%), "DL_XSPOR" (5.09%), "DL_XELKT" (4.91%), and "DL_XBANK" (4.87%). Moreover, the value of skewness shows that all stock indices have a left-skewed distribution, i.e. they are negatively skewed and their left tail is longer than the right tail. Conversely, skewness value of "DL_TR2YGB" (0.70) indicates a positive-skew distribution where the right tail is longer than the left tail and the average value, –0.10%, is to the right of the median, –0.18%, value. Since kurtosis value of all variables is greater than 3, it is said that they possess a leptokurtic behavior and have fat tails and peakedness. Therefore, taken both the value of skewness and kurtosis no variables follow normal distribution, corroborating the results of the Jarque-Bera test.

Figure 2: Multiresolution Analysis (MRA) of DL_TR2YGB vs. DL_XU100

The results of the ADF (1979), the KPSS (1992) and the PP (1988) unit root tests are given in Table 2. Evidently, the ADF (1979) test shows that all variables while the PP (1988) illustrates that with the exception for "LXILTM" and "LXTRZM", all variables have unit root. On the contrary, the null hypothesis of stationarity for the KPSS (1992) can be rejected for "LXTAST" and "LXTRZM", indicating the presence of unit root for the other variables. Since there is not any consensus on the stationarity, we applied these tests on the log-differenced data.

Figure 3: Wavelet Variance and Correlation by Scale
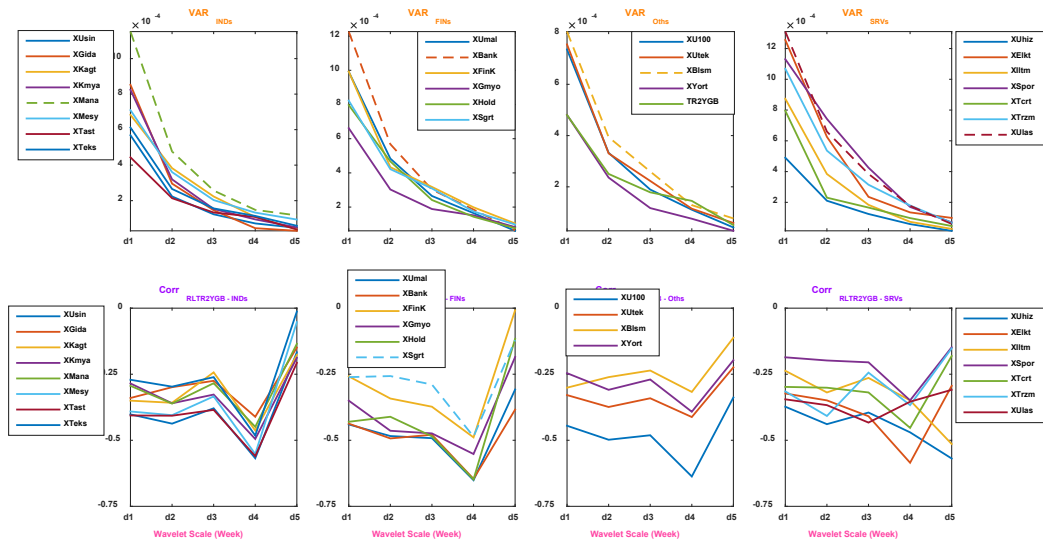
Accordingly, the presence of a second unit root can be rejected for the log-differenced data at the 1% significance level, i.e. all variables are integrated of order one, $I(1)$.

In order to obtain wavelet coefficients, the stationary observations are decomposed into several wavelet scales applying the "MODWT" with the Daubechies [LA(8)] wavelet filter. The wavelet decomposition and significance test is performed with the "Waveslim" and the "Brainwaver" R (2006) packages introduced by Whitcher (2005) and Achard (2012), respectively. Although the achievable level of "MODWT" is $9 \leq \log_2 (604)$, the optimal integer decomposition level is chosen as $J=5$, since the number of feasible, non-boundary effected, wavelet coefficients decline gradually as scale increases. Contrary to wavelet coefficients, the multiresolution detail coefficients generated by "MRA" function is the same at each decomposition level where periodic boundary condition is chosen. After decomposition process, we obtain five levels of detail components and one smooth component for "MRA": d1+d2+d3+d4+d5+s5 and five levels of wavelet components and one scaling component for "MODWT": w1+w2+w3+w4+w5+s5. These decomposition levels are corresponding to [2-4) weeks for "d1" (w1), [4-8) weeks for "d2", [8-16) weeks for "d3", [16-32) weeks for "d4", [32-64) weeks for "d5", and [64-N) weeks for "s5".

The multiresolution decomposition analysis (MRA) for "DL_TR2YGB" and "DL_XU100" is depicted in Figure 1. At the top, the original return series are exhibited. The most noticeable observations are that "TR2YGB" significantly fluctuated by 14.3% before the FED monetary decisions on June 23, 2006 and by 13.06% during the GFC on November 24, 2008. However, the most highest increases, 14.57% and 19.52%, are observed during the domestic developments. The most peak decreases, –10.99% and –13.61%, however, are witnessed due to the positive improvement in both the domestic and foreign markets in September 2013 and January 2015, respectively. Conversely, the most

prominent fluctuations in "XU100" are observed in 2008 where stock market slipped by –19.27% on October 10, 2008 but almost regained its loss at the end of the same month increasing by 14.08%. Moreover, the most peak increase, 15.76%, is observed on November 28, 2008 just after one week when the stock market decreased by –14.62%, which is the second peak value.

The third highest decline seen in the previous years, however, is the –14.37 percentage shrinkage due to the failed coup attempt in July 2016. On the other hand, the six plots below the original data show the "MRA" of five detail components and one smooth component in ascending order, from the finest time-scale (M1) to the coarsest time scale (M5), for each variable. Obviously, the resolution quality noticeably decreases as scale level increases. The detail components "M1" and "M2" largely can illustrate the major fluctuations while the crystals "M3", "M4" and "M5" are not as successful as the finest two components at showing discernible movements, which observed at the original data of the two series. Equivalently speaking, the effect of aforementioned fluctuations has lasted over two scale levels with cycles of up to 8 weeks. Lastly, it is quite apparent that the smooth component, "M5S", indicating a trend, does not capture any distinct fluctuations in the underlying variables.

After decompose return series into time-scales by "MODWT()" function, we obtained unbiased wavelet estimation for variance and correlation for all underlying variables. Figure **3** shows that wavelet variance is depicted in the upper panel while wavelet correlations is plotted in the bottom panel. There are two noteworthy findings emerge from the figure. First, it is quite clear that wavelet variance declines from the finest time-scale, "d1", to the coarsest time-scale, "d5", i.e. the higher time-scale the lower wavelet variance for all stock index groups, suggesting an approximate inverse linear linkage between time horizons and wavelet variances. These results indicate that the highest volatility in changes in bond yields and stock prices take place at the finest scale, "d1", corresponding to over 2 to 4 weeks. The highest volatile variables at scale "d1" are "DL_XULAS" (0.131%), "DL_XELKT" (0.126%), and "DL_XBANK" (0.123%), while, the lowest volatile ones are "DL_XTAST" (0.044%), "DL_TR2YGB" (0.04801%), and "DL_XYORT" (0.04806%). Moreover, "DL_TR2YGB" is at 21st, 18th, 10th, and 16th rank at scale d2, d3, d4, and d5, while "DL_XU100" is at 17th, 15th, 15th, 17th, and 20th rank at from the finest to coarsest scales, respectively.

Since each detail component has zero mean, the energy of each component will be equal to the variance of the detail coefficients, therefore, the variance of the original data is the sum of the wavelet variances. Therefore, we can study variance decomposition by time-scale as the energy distribution for the data under investigation. It is obvious from the figure that the most of the energy distribution (cumulative variances to total variance) is concentrated on the finest scales regardless of the return series considered. The first three variables that has the highest energy distribution at scale "d1" are, for example, "DL_XGIDA" (60.52%), "DL_XTCRT" (57.07%), and "DL_XILTM" (55.82%), while, "DL_TR2YGB" (40.60%) is at 26th, "DL_XMESY" (42.47%) is at 25th, and "DL_XSPOR" (42.91%) is at 24th rank. At the medium scale, "d3", the energy decomposition reaches up to 92.13% for "DL_XILTM", 91.90% for "DL_XGIDA", and 88.55% for "DL_XUHIZ", while, on the other hand, "DL_XMESY" (76.23%), "DL_TR2YGB" (76.86%), and "DL_XGMYO" (76.85%) have the lowest percentage energy distributions over 8 to 16 weeks. In addition, the services sector indices are the most volatile up to the scale "d3" and the industrial sector indices are the least volatile. These findings

indicate that investors with short-term investment horizons are confronted by higher risks than investors with longer-term holding periods. Our results are in accordance with the findings of Lee (2004), Fernandez (2005), Çifter and Özün (2007) and Dajcman (2013) in terms of energy decomposition and variance-scale relation. For example, Çifter and Özün (2007) find out a negative relationship between time-scales and wavelet variance of "DL_XU100", "DL_XU030" and a list of individual stock returns in Turkey. Test findings also show that their energies concentrated over [2-4) days for "d1", namely, the energy distribution is 51.35% for "DL_XU030", 51.18% for "DL_XU100", and 42.46% for "DL_TUPRS". Similarly, their energy decomposition reaches up to approximately 90% for both "DL_XU030" and "DL_XU100", 86% for "DL_TUPRS" over [2-16) days. In addition to inverse relationship between wavelet variance and time-scale, Dajcman (2013) documents that most of volatility of stock indices of "FTSE100" (91.8%), "CAC40" (91.3%), "DAX" (90.0%), and "ATX" (90.0%) is captured by the finest three scales corresponding to [2-16) days. The background behind this finding is interpreted as the higher investment horizons the less rapid adjustment to fluctuations, namely, investors with shorter-term horizons should react rapidly to stock market fluctuations for their portfolio adjustments. Differently saying, the importance of volatility varies for investors with heterogeneous investment horizons because every investor essentially deals with different dynamics. Lee (2004) finds out that nearly 90 percentage of energy distributions of both "KOSPI" and "DJIA" indices are observed at the first three time-scales, indicating that short-term noise variations are the major factors in explaining equity returns, accordingly, equity returns cannot be forecasted beforehand. Fernandez (2005), on the other hand, reports approximately 75 percentage and 64 percentage of energy distribution at scales "d1" and "d2" in the volatility of stock markets in the North American and Emerging Asian countries, indicating that movements in stock returns are mostly observed in the shorter-term horizons.

Table 3: Significance of Correlation Coefficients by Wavelet Scale

Variable	Return		d1		d2		d3		d4		d5	
RXU100	-0.484	***	-0.445	***	-0.498	***	-0.481	***	-0.637	***	-0.338	
RXUMAL	-0.485	***	-0.440	***	-0.484	***	-0.492	***	-0.651	***	-0.308	
RXBANK	-0.484	***	-0.437	***	-0.493	***	-0.479	***	-0.646	***	-0.384	
RXFINK	-0.325	***	-0.258	***	-0.342	***	-0.373	***	-0.489	***	-0.008	
RXGMYO	-0.427	***	-0.350	***	-0.464	***	-0.474	***	-0.552	***	-0.185	
RXHOLD	-0.450	***	-0.430	***	-0.411	***	-0.485	***	-0.648	***	-0.116	
RXSGRT	-0.298	***	-0.261	***	-0.257	***	-0.289	**	-0.486	***	-0.121	
RXUSIN	-0.413	***	-0.402	***	-0.437	***	-0.379	***	-0.568	***	-0.167	
RXGIDA	-0.324	***	-0.340	***	-0.299	***	-0.275	**	-0.411	**	-0.149	
RXKAGT	-0.362	***	-0.350	***	-0.358	***	-0.243	**	-0.463	***	-0.177	
RXKMYA	-0.321	***	-0.285	***	-0.36	***	-0.327	***	-0.495	***	-0.188	
RXMANA	-0.301	***	-0.294	***	-0.361	***	-0.284	**	-0.449	***	-0.135	
RXMESY	-0.395	***	-0.391	***	-0.405	***	-0.334	***	-0.552	***	-0.053	
RXTAST	-0.423	***	-0.406	***	-0.407	***	-0.385	***	-0.56	***	-0.207	
RXTEKS	-0.311	***	-0.271	***	-0.297	***	-0.261	**	-0.482	***	-0.013	
RXUHIZ	-0.401	***	-0.373	***	-0.439	***	-0.395	***	-0.47	***	-0.569	**

RXELKT	-0.369	***	-0.323	***	-0.349	***	-0.409	***	-0.585	***	-0.294		
RXILTM	-0.276	***	-0.237	***	-0.319	***	-0.264	**	-0.349	**	-0.514	**	
RXSPOR	-0.206	***	-0.186	***	-0.198	**	-0.205	*	-0.349	**	-0.148		
RXTCRT	-0.310	***	-0.298	***	-0.301	***	-0.319	***	-0.453	***	-0.181		
RXTRZM	-0.329	***	-0.315	***	-0.408	***	-0.244	**	-0.367	**	-0.152		
RXULAS	-0.380	***	-0.345	***	-0.367	***	-0.433	***	-0.354	**	-0.309		
RXUTEK	-0.352	***	-0.329	***	-0.374	***	-0.341	***	-0.412	**	-0.224		
RXBLSM	-0.291	***	-0.301	***	-0.261	***	-0.236	**	-0.317	*	-0.112		
RXYORT	-0.300	***	-0.246	***	-0.309	***	-0.27	**	-0.392	**	-0.197		

*,**, and *** indicate 10%, 5%, and 1% significance level, respectively.

Second, as expected and in common with the existing literature we discovered that stock market indices, with some exceptions, are more volatile than bond market up to scale "d3", indicating that investors in stock markets cope with higher risk compared to bond market participants. This finding is in line with the Kim and In (2007) for G7 countries except for Japan, Moya-Martínez et al. (2015) for Spanish stock indices and Dajcman (2015) for ten Eurozone countries.

In addition to wavelet variance, test findings of the wavelet correlations also are exhibited at the bottom panel in Figure **3**. The main observation is that there exists negative association between changes in bond yields and stock returns regardless of the investment horizons and sectors. Moreover, the significance test results are reported in Table 3Table 3, in which the relationship is significantly negative at contemporaneous for the raw return series and wavelet scales up to scale "d4", with exceptions for "DL_XUHIZ" and "DL_XILTM" over [32-64) weeks.

Evidently the highest negatively sensitive indices to interest rate changes, not surprisingly, are from the financial group, i.e. "DL_XUMAL" (-0.4849), "DL_XBANK" (-0.4841), "DL_XU100" (-0.4837), "DL_XHOLD" (-0.4504), and "DL_XGMYO" (-0.427), while the lowest significantly sensitive, as expected, indices are "DL_XSPOR" (-0.2059), "DL_XILTM" (-0.2757), and "DL_XB-LSM" (-0.2910), for contemporaneous correlations. Moreover, it can be seen that the most negatively sensitive indices are the same over all wavelet scales. At scale "d1" they are "DL_XU100" (-0.445), "DL_XUMAL" (-0.440), and "DL_XBANK" (-0.438); at scale "d2" they are "DL_XU100" (-0.499), "DL_XBANK" (-0.494), and "DL_XUMAL" (-0.494); at scale "d3" they are "DL_XUMAL" (-0.492), "DL_XHOLD" (-0.485), and "DL_XU100" (-0.481); and at scale "d4" they are "DL_XU-MAL" (-0.651), "DL_XHOLD" (-0.649), and "DL_XBANK" (-0.647). Evidently, negative correlation coefficients moderately increased absolute value at scale "d2", remained the same at scale "d3", while considerably increased at scale "d4" and again noticeably decreased at the coarsest scale "d5". On the other hand, the minimum (-0.008) and maximum (-0.65) correlation coefficient are witnessed at scale "d4" for "DL_XUMAL" and scale "d5" for "DL_XFINK". These findings suggest that the negative relationship between changes in interest rates and stock returns are mostly pronounced over the medium investment horizon corresponding to [16-32) weeks. The evidence of negative relationships presented here are corroborating the findings of Kim and In (2007) for G7 countries, Moya-Martínez et al. (2015) for Spanish stock indices and Dajcman (2015) for Eurozone countries.

In order to shed light on the potential lagged impacts on the stock-bond relationship, Figure **4** displays the results of the MODWT-based cross-correlation estimations at time t-τ and t-τ up to 24-week time lags for the five time-scale levels. The black lines indicate wavelet correlation estimations while the green and red dashed lines represent the approximate upper and lower confidence intervals at 95% levels, respectively. Moreover, the left-hand side reveals causal association "DL_TR2YGB" ⇏ "DL_X" while the right-hand side shows the opposite association.

Evidently, there are insignificant relationships between underlying variables at the finest wavelet scales. As wavelet scales increases, however, statistically significant linkages arise. Notably, the cross-correlation relationship is the same for "DL_XU100" and "DL_XUMAL" indices, suggesting that the financial indices are the main driver of the main stock index, "XU100". In addition, the highest and statistically significant negative correlations are obtained at zero lags for all return pairs. Not surprisingly, there also exist positive cross-correlations over scales since shifting one variable between two negatively correlated variables might generate positive movements. Stock returns and changes in bond rates move in the same direction about at 1, 2-3, 4-7 and 8-14 weeks over the first 4 scales, "d1" to "d4", namely, both variables positively leads each other up to the fourth scale. Conversely, they move in the opposite direction roughly at first several lag intervals. The evidence of statistically significant interdependence between bond and stock markets in Turkey presented here is broadly in line with the results of Hamrita and Trifi (2011), Abdullah et al. (2014), and Moya-Martínez et al. (2015). Abdullah et al. (2014), for example, documents positive linkages between Kuala Lumpur Composite Index and short-term interest rates at scale levels 2 and 4, corresponding to 2-16 months, i.e. the short-term rate lead stock index in the long run. Similarly, the author (2014) finds insignificant linkage between long-term rates and stock index at wavelet scales "d1", "d2", and "d4". However, they positively related at scale "d3", namely stock index leads government bond rates over period of 4-8 months. Furthermore, Hamrita and Trifi (2011) report statistically insignificant relation between interest rate and stock index at shortest wavelet scales in the US, however, it turns out to be significant at coarsest scales, namely they highlight a positive leading association in the long run. Moya-Martínez et al. (2015), on the other hand, find that the magnitude of the relationship increases with the scale levels. Likewise, the association is significant at both sides regardless of the sectors at the longer scales. Equivalently speaking, changes in 10-year bond rates leads industry returns while the opposite holds true as well. The reason behind these findings is that true dynamic of relationship is determined in the long term since the association is largely driven by sporadic events, shocks, psychological factors, and changes in market sentiment in the short-term. The association, however, becomes stronger in the long-term since stock markets are influenced by macroeconomic factors. Therefore, it is expected to have significant relationships and affect each other in the long term because they are close substitutes for investors.

Conclusions

In this paper, we aimed to reexamine the stock-bond relationship using weekly observations of government bond yields and industry returns over a sample period between April 1, 2005 and December 30, 2016. In order to shed light on the true dynamics of relationship, we implement

frequency-based methodology, wavelets, since we believe that with standard econometric method one cannot dig out true dynamics of the bond-stock association. Implementing wavelet methodology, we offer a deeper understanding about this relationship by considering both the aggregate and industry level since, as noted by Müller et al. (1993), each component of markets has a different investment horizon and characteristic dealing frequency, and operate at multiple time-scales and reacts differently to the same information in the same market than other components. Besides, they have different degree of risk aversion, face with different transaction costs, and institutional constraints. Since the memory of volatility of the whole market is comprised of each component's volatility, a need arises to study their effects on overall market, and therefore, to present valuable information for their trading strategies, which is the main motivation of the paper.

Test findings of paper reveal that all weekly returns are close to zero. The average return of stock returns is positive while change in bond yields is negative, indicating a poor performance for bond market instruments. Over tested period, the most successful and unsuccessful indices in terms of weekly average returns are the same: "DL_XSPOR", "DL_XFINK", and "DL_XELKT". As expected and in common in existing literature, stock market (3.80%) is more volatile than bond market (3.39%). Not surprisingly, the most volatile variables are among the variables that have minimum and maximum average weekly returns: "DL_XULAS" (5.24%), "DL_XSPOR" (5.10%), "DL_XELKT" (4.90%), "DL_XBANK" (4.87%), and "DL_XTRZM" (4.80%). Notably, stock indices are, 17 out of 24, found to be more volatile than the aggregate stock market index. Moreover, stock indices have a left-skewed distribution while bond yields are positively skewed and their right tail is longer than the left tail. All variables, on the other hand, posses a leptokurtic behavior, have fat tails and peakedness. Thus, they do not follow normal distribution, which is in common for financial variables.

In order to analyze frequency-based behavior of variables, their stationary series are decomposed by the "MODWT" with the Daubechies LA(8) wavelet filter. The optimal integer decomposition level is preferred as five although the achievable level is nine. The decomposition levels denote [2-4) weekly periods for "d1", [4-8) for "d2", [8-16) for "d3", [16-32) for "d4", [32-64) for "d5" detail, and [64≤) for "s5" smooth component. Our findings show that wavelet variances decline regardless of variables as scale level increases. The most energy of variables is captured by the finest scales. For example, the highest energy decompositions at scale "d1" are observed for "DL_XGIDA" (60.52%), "DL_XTCRT" (57.07%), and "DL_XILTM" (55.82%). The cumulative energy reaches up to 81.5% for "DL_XGIDA", 80.4% for "DL_XILTM", and 76.1% for "DL_XELKT". Overall, at least 76% of volatilities of all returns can be explained by short run dynamics, namely, the short run dominates the long run in terms of energy distribution. These findings indicate that short-term and long-term investors face intrinsically different dynamics that should be taken account for risk management. Market volatilities driven by changes in market sentiments, psychological and technical factors in the short-term are less important for long-term investors because longer-term fundamental information set dominates markets as investment horizon increases.

In order to study comovement and spillover transmission between bond and stock market, wavelet correlation and cross-correlations are estimated. As expected, there exist significantly negative relationships between changes in bond yields and industry returns over scales. As level increases,

the degree of correlation also increases. The highest correlations are observed for financial indices; for example, it is –0.446 for "DL_XU100", –0.440 for "DL_XUMAL", and –0.439 for "DL_XBANK" at scale "d1" while it rises to –0.638, –0.651, and –0.647 at scale "d4" for the same indices. These findings provide strong evidence that return comovement between bond and stock market is a multiscale phenomenon and the extent of relationship varies slightly across industries over scales. Therefore, it can be said that all indices benefit from falling interest rate by decreasing cost of borrowing and increasing share prices and vice versa in Turkey. Furthermore, in line with existing theory and evidence, these results show that financial sector is the most sensitive to interest rate movements. On the other hand, cross-correlation estimations reveal significantly positive and negative bidirectional lead-lag relationships in the longer-time horizons. Thus, one can estimate current value of one variable by using past value of another variable.

Overall, test results show that both instruments can be used as hedging tools since they are perfect substitutes for investors in the case of market turbulences. However, negative relationship does not allow investors to follow tactical asset allocation strategy. Besides, the strengthening inverse relationship provides a better portfolio diversification at higher time horizons. Short-term investors are advised to react to each variation in returns given that the highest portion of energy decomposition is concentrated on the short run and the finest wavelet scales are accepted to be related to speculative activities. The coarsest scales, on the other hand, are thought to be related to investment activity, therefore, long-term investors are advised to not respond to each movement in returns in the short time. Similarly, the policy-maker should take into account the correlation and causal relationships at different time horizons before implementing policy rate decisions and should be patient for their consequences to secure the resiliency and durability of the financial system.

Figure 4: Wavelet Cross-Correlation by Scale
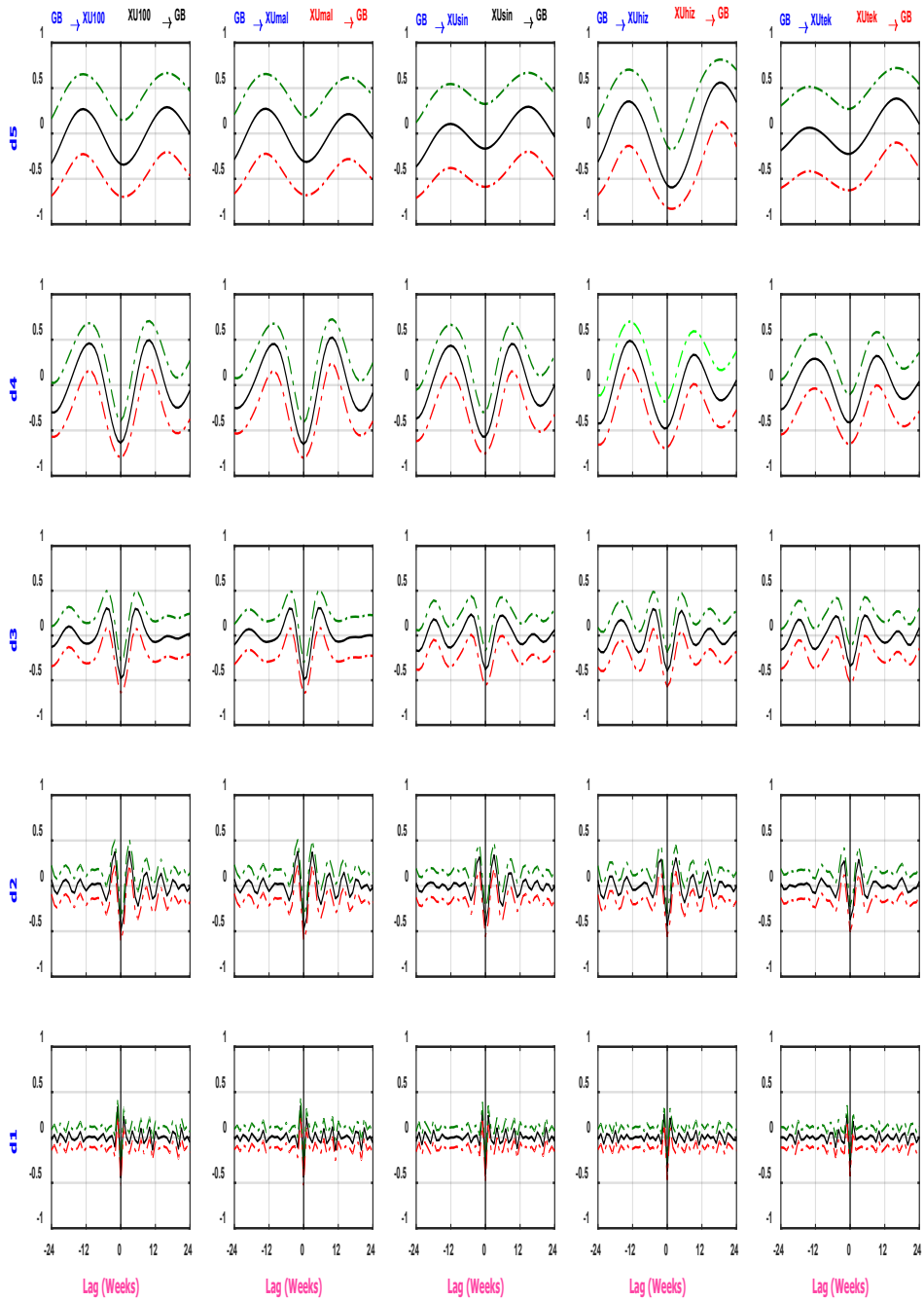
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