INVESTIGATING THE DYNAMIC RELATIONSHIP BETWEEN WIND SPEED AND STOCK MARKET RETURNS: EVIDENCE FROM BORSA ISTANBUL

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ABSTRACT

The main approach of behavioral finance is to highlight the influence of psychological factors on investors' decisions. In this direction, the effects of meteorological events on human behavior have been examined across various disciplines and also hold a significant place in many cultural belief systems. This study investigates the causal relationship between wind speed and stock market returns in Borsa Istanbul from 2005 to 2020, taking seasonal variation into account. To achieve this, time-varying symmetric and asymmetric causality tests were employed. The findings of the time-varying symmetric causality test reveal significant causal relationships, particularly during the 2005–2006 and 2011–2012 periods. The asymmetric test results suggest that positive wind shocks may reduce returns in autumn and winter seasons, while negative wind shocks may cause an increase in returns during the winter months. These results indicate that weather conditions may contribute to short-term fluctuations in financial markets. Therefore, it is important for policymakers to develop measures aimed at enhancing market stability by taking weather-induced changes into consideration. Investors, on the other hand, may make more informed decisions by integrating seasonal and meteorological factors into their investment strategies. In this regard, the study is among the pioneering works that examine the dynamic relationship between wind speed and stock market returns while accounting for seasonal effects.

ÖZ

Davranışsal finansın temel yaklaşımı, yatırımcı kararlarında psikolojik faktörlerin etkisini ortaya koymaktır. Bu doğrultuda, meteorolojik olayların insan davranışları üzerindeki etkisi farklı disiplinlerce incelenmiş ve birçok kültürel inanışta da önemli bir yer edinmiştir. Bu bağlamda çalışmanın amacı, 2005-2020 döneminde Borsa İstanbul için rüzgâr hızı ile borsa getirileri arasındaki nedensel ilişkiyi mevsimleri de dikkate alarak incelemektir. Bu amaçla zamanla değişen simetrik ve asimetrik nedensellik testleri kullanılmıştır. Zamanla değişen simetrik nedensellik testinin bulguları özellikle 2005-2006 ve 2011-2012 dönemlerinde baskın nedensel ilişkiler olduğunu göstermektedir. Zamanla değişen asimetrik nedensellik testinin bulguları ise pozitif rüzgâr şoklarının sonbahar ve kış aylarında getirilerde azalmaya, negatif rüzgâr şoklarının ise kış aylarında artışa neden olabileceğine işaret etmektedir. Elde edilen bulgular, hava koşullarının finansal piyasalarda kısa vadeli dalgalanmalara yol açabileceğini ima etmektedir. Bu nedenle politika yapıcıların, hava kaynaklı değişimleri dikkate alarak piyasa istikrarını artıracak önlemler geliştirmeleri önemlidir. Yatırımcılar ise, mevsimsel ve meteorolojik faktörleri yatırım stratejilerine entegre ederek daha bilinçli kararlar alabilirler. Bu yönüyle çalışma, rüzgâr hızı ile borsa getirileri arasındaki dinamik ilişkiyi mevsimsel etkileri de dikkate alarak inceleyen öncü çalışmalardandır.

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INTRODUCTION

The impact of natural environmental conditions on human psychology and social decision-making processes has been observed in many cultures throughout history and has led to various measures being taken. For example, meteorology and disaster management expert Kadıoğlu (2019) has pointed out that southwesterly winds, known as 'Lodos' in Turkish, cause psychological effects such as tension, depression, and restlessness in people, and emphasized that this effect was taken seriously enough to influence official decision-making processes in both the Byzantine and Ottoman periods. Furthermore, in 2008, the police apprehended a criminal network that exclusively operated during southerly weather conditions (Yenişafak.com, 2008). In a study where localized trading proxy variables were used, no significant effect was found on firm-specific stock returns and behaviors related to stocks in the presence of hot, dry, strong, and harsh winds like the Santa Ana Winds in Southern California. An excerpt from Raymond Chandler's work 'The Red Wind' is quoted as follows (Saporoschenko, 2011):

"… those hot dry winds that come down through the mountain passes and curl your hair and make your nerves jump and your skin itch. On nights like that every booze party ends in a fight."

In contrast to the concept of *homo economicus*, it can be argued that there is a direct relationship between the behaviors and psychology of normal individuals (Firli & Rahadian, 2018). When individuals experience temporary fluctuations in their moods, emotional states, expectations, and risk perceptions, these changes can significantly affect their economic decision-making processes (DellaVigna, 2009) and lead to both optimal and suboptimal behavior (Kang et al., 2019). Currently, there is a growing body of literature in economics, finance, and marketing that expands on this premise (Sandqvist & Siliverstovs, 2021). Additionally, a substantial body of research exists regarding the general psychological, physiological, and cognitive effects of weather conditions and even spatial events (Howarth & Hoffman, 1984). In this context, one of the intersections of this relevant literature suggests that in the field of behavioral finance, especially, short-term stock returns and volatility may be influenced by meteorological factors (Limpaphayom et al., 2005). In a comprehensive analysis, Khanthavit (2017) reported the effects of temperature, cloud cover, rainfall, relative humidity, wind speed, air pressure, and ground visibility on stock returns. Similarly, in a study where various factors such as temperature, wind speed, humidity, sunshine hours, and cloud cover were tested, similar relationships were identified, with temperature being the primary determinant (Gunasekara & Jayasinghe, 2019). Furthermore, a statistical relationship has been reported between stock returns and a wide range of meteorological variables such as rainfall, changes in daylight hours, seasonal fluctuations, and lunar phases (Dowling & Lucey, 2005). It is reported that stock analysts' reactions to adverse weather conditions are less frequent and slower compared to favorable conditions (Dehaan et al., 2017). The announcements related to monsoon rains have also been reported to have an impact on cumulative average abnormal returns (Nagarajan et al., 2021). Furthermore, it has been reported that the changes in the mental states of adults due to weather conditions also affect children in the 3-6 age range, with a significant relationship, particularly in terms of internalizing, externalizing, and prosocial behaviors (Lagacé-Séguin & d'Entremont, 2005). However, findings from a country like Finland, where daylight duration and sunlight can be considered extreme, suggest that weather conditions have relatively weak explanatory power for these economic behaviors. It is also known that individuals engage in fewer transactions during holiday periods (Kaustia & Rantapuska, 2016). Weather variables used for New York and London have no significant impact on stock and currency markets during the period of 2002-2018 (Andrikopoulos et al., 2019).

The findings in the psychopathology literature related to behavioral and neurofinance appear to complement those related to mood due to weather conditions. One of the most notable studies on the relationship between meteorology and behavioral finance is by Cao & Wei (2005). They report that abnormal (low or high) temperatures are associated with aggression; high temperatures lead to indifference; and low temperatures correspond to high returns, whereas high temperatures correspond to low returns. From this perspective, indifference, similar to what is observed in individuals with a history of depression and suicide in the literature, could potentially lead to a lack of motivation in risk-taking behavior (Baek et al., 2017). On the other hand, considering that aggression can also influence risk-taking behavior, this aligns with what has been reported in the context of psychopathology, particularly in bipolar and manic disorders (Lasagna et al., 2021). It has been reported that extreme daily weather fluctuations can affect investors' moods and sensitivity, increasing volatility in returns (Shim et al., 2017). For example, one study conducted on emerging economies indicates that temperature has a significantly negative impact on stock returns in these markets (Mirza et al., 2012). Furthermore, similar effects have been observed in developed European countries (Floros, 2008). The impact appears to be sector-specific, extending to market returns (Schulte-Huermann, 2020). Evidence suggests a negative relationship between temperature increases and stock returns, with reports of positive effects of cold months like January on returns in relatively warm climates such as Portugal (Floros, 2011). It is reported that temperature and cloud cover affect stock returns, with returns tending to be lower during extreme temperature fluctuations or when cloud cover is very dense (Chang et al., 2006). Rain or snowfall may show no significant relationship with stock returns, but morning daylight has been strongly associated with them (Hirshleifer & Shumway, 2003).

In this regard, meteorology is used as a mood-proxy variable to understand the financial behavior of the masses (Li & Peng, 2016). Given that meteorological conditions can influence individuals' psychology, they may also indirectly affect their financial behavior (Khanthavit, 2017). In other words, if weather conditions affect individuals' moods and, in turn, affect financial behavior (Wright & Bower, 1992), then it would not be an erroneous expectation to predict a correlation between meteorology and financial behavior. For instance, it has been reported that sunny weather can induce optimism in individuals, and this optimism can increase investors' willingness to take long positions (Symeonidis et al., 2010). Furthermore, whether weather conditions are normal or extreme may affect mood, intuition, and beliefs, thereby altering investment behavior. Although the effects of weather fluctuations are known, this study aims to contribute to the literature by examining relatively understudied instantaneous or daily weather changes, in addition to the well-established impacts of climate (Shahzad, 2019) and season (Keller et al., 2005) on financial behavior. The motivation for this study is based on various reasons, and the existing literature on the relationship between weather conditions and psychology, physiology, and the cognitive system within the scope of behavioral finance contributes to this motivation. For instance, changes in behavior related to changes in weather conditions are linked to alterations in the central nervous system, primarily involving neurotransmitters, such as serotonin, due to changes in atmospheric electricity and ion concentration in the air (Sher, 1996). Considering that serotonin modulates aspects such as decision-making, probability assessment, delay discounting, risk, self-control, and cooperation (Nadler & Zak, 2016), it is possible to gain some insight into the connection between weather conditions and financial behavior through this link. On the other hand, anxiety is directly related to loss avoidance (Charpentier et al., 2017) and risk avoidance (Maner et al., 2007), which means that weather-induced anxiety has the potential to naturally influence financial behavior.

Additionally, meteorology affects individuals not only at the psychological level but also through sensory perceptions. Changes in air pressure are perceived by the ears, and variations in light are perceived as a visual stimulus for the sense of sight (Lu & Chou, 2012). Wind can trigger respiratory problems and migraines (Saporoschenko, 2011). In addition to its psychological and physiological effects, meteorology is also believed to impact the body's circadian rhythm (Leger, 1994). One of the most common disorders is Seasonal Affective Disorder (SAD), which arises from changes in total daylight due to the Earth's rotation around the sun (Rosenthal, 2012). SAD has direct effects on economic and financial behaviors, including risk attitude (McAndrew, 1993), stock prices (Dowling & Lucey, 2008), and returns (Kamstra et al., 2003).

In addition to the aforementioned effects on mood and behavior, it has been reported that weather conditions also have some influence on cognitive processes. Weather that induces positive mood can indirectly facilitate cognitive processes, leading to quick decision-making without much deliberation (Isen, 1993). It can also promote optimism and a greater propensity for risk-taking (Johnson & Tversky, 1983). In contrast, a negative mood may produce positive effects on memory (Forgas et al., 2009) or prediction errors (Majewski & Mentel, 2022). Therefore, if weather conditions and meteorological events can influence individuals psychologically, physiologically, and even pharmacologically, it should not be surprising that some indirect effects can be observed in their economic behavior, at the very least. This study investigates the relationship between stock market returns of the Istanbul Stock Exchange (BIST-100) and prevailing wind speed in Istanbul. In this study, we dynamically use these tests to account for changes in the causal relationships in the sub-samples. Thus, the study fills an important gap by bringing a dynamic perspective to the relationship between weather and financial markets, which has been addressed in the literature mostly with static approaches. Existing studies have generally examined the effects of meteorological variables such as temperature, humidity, cloud cover, and wind on financial indicators using general models, but they have not sufficiently considered how these relationships change over time, how they differ depending on the direction of shocks, and how seasonal effects operate. The first contribution of this study is its examination of the relationship between wind speed and Borsa Istanbul returns within a time-varying structure, and its identification of the periods in which this causal relationship emerges using dynamic symmetric and asymmetric causality tests. The primary advantage of dynamic causality tests is their ability to identify the periods in which causality exists. Furthermore, the proposed asymmetric dynamic causality tests have superior features compared to their alternatives. For example, the Quantile-on-Quantile approach is useful for addressing asymmetries, but our approach accounts for both asymmetries and instabilities. The second contribution is that it reveals direction-dependent (asymmetric) responses in investor behavior by separately analysing the effects of positive and negative wind shocks. In this respect, the study is one of the few that tests the investor sensitivity effect predicted by behavioral finance theory in a seasonal context. The third contribution is that it includes seasonal differences in the model, revealing that the effect of wind varies, especially in autumn and winter. This shows that climatic effects cannot be considered in a one-dimensional manner and that seasonal disaggregation has analytical value. The fourth and perhaps most important contribution is that it is the first to address the effect of an environmental variable such as wind speed, which is often overlooked in developing markets such as Turkey, on stock market returns using time- and shock-sensitive dynamic tests. In this context, the study offers an innovative methodological approach to the literature and fills an important gap specific to Turkey at the regional level.

The remainder of this article is organized as follows: Chapter 2 discusses the impact of meteorological events on stock trading behavior and performance and reviews the relevant literature. Chapter 3 explains the data and provides summary statistics. Chapter 4 presents the empirical results, and Chapter 5 concludes the paper.

LITERATURE REVIEW

Studies analyzing the effects of weather events on the stock market have been examined. In order to reveal whether the results differ according to countries, the studies are categorized by country. For example, in studies conducted in the US, Hou et al. (2019) found that stock returns decrease in hot weather as investors take less risk. Lanfear et al. (2019) showed that extreme weather events have a significant impact on market anomalies. Griffin et al. (2019) demonstrated that extreme temperature events negatively affect companies' profitability and investors' perception of risk. Jiang et al. (2021) reported that earnings announcements prior to adverse weather conditions delay market reactions. Kruttli (2025) documented that hurricanes affect the expected stock returns of affected companies. Altin (2024) indicated that extreme weather events generate greater volatility in the S&P 500 return index than positive market news. Furthermore, Shu& Fan (2024) found that firms perceive extreme weather events as a serious risk.

In studies for European countries, Schulte-Huermann (2020) reported that weather conditions do not affect the stock market returns of all sectors in Germany in the same way. Muhlack et al. (2022) showed that in Germany, weather pressure reduces trading volume on the SDAX and TecDAX, while changes in weather pressure led to increases in returns on the DAX, MDAX, and SDAX. Tarczyński et al. (2021) found that there is no significant relationship between weather and stock returns on the Warsaw Stock Exchange. Bertrand and Chabot (2020) demonstrated that weather-related announcements have little effect on returns. Peillex et al. (2021) documented that in France, extreme temperatures significantly reduce trading volume. Finally, González-Sánchez et al. (2024) provided evidence that temperature shocks—both hot and cold—distort the risk premium.

In studies conducted for China, Shahzad (2019) showed that weather conditions have a significant impact on stock market returns and volatility. Jiang et al. (2019) found that disruptive events such as typhoons and hurricanes in the Hong Kong and Shenzhen stock markets have a significant negative impact on returns. Huang et al. (2020) reported that air pollution and fog reduce individual trading activity. Chen et al. (2024) concluded that extreme weather conditions have a significant negative effect on stock returns. The study for Korea by Cin et al. (2020) indicated that weather does not significantly affect industrial stock returns in the Korean market but may influence volatility. Kathiravan et al. (2021) revealed that weather significantly affects investor sentiment in Asian stock markets. Chowdhury (2024) showed that weather significantly shapes investment decisions in South Asian countries. In a study for Canada, U-Din et al. (2022) found that the severity and frequency of weather events have a significant negative impact on stock market returns. Antoniuk and Leirvik (2021) demonstrated that climate change policy events significantly affect returns on a global scale. Saura et al. (2023) reported that extreme weather conditions globally affect various domains, including the stock market. Kmetz et al. (2024) showed that extreme weather events worldwide significantly increase financial market uncertainty.

In studies conducted for Turkey, Medetoğlu and Kavas (2022) found that seasonal temperature changes affect BIST ALL Index prices in their analysis based on the example of Istanbul. In particular, significant relationships were found between air temperature and index prices in the summer and spring months. Similarly, Güngör&Küçün (2022) investigated the impact of weather conditions on investment decisions and reported that variables such as air pressure, temperature, and humidity significantly affect both trading volume and the number of transactions. This study revealed that environmental conditions can affect markets through investor sentiment. Gündoğdu and Sarılı (2021), in a panel data analysis covering six countries (Turkey, Italy, the United States, Canada, China, and Russia), found that weather anomalies were only long-term correlated with stock indices in Canada and Russia. These results indicate that the effect of weather conditions may vary by country. Güngör and Küçün (2019) determined that trading volume and trading volume in the BIST100 index differed on sunny and rainy days. In particular, trading volume was significantly lower on sunny days, which was explained by investors redirecting their savings to different areas during holiday periods. This shows that investor preferences are sensitive to seasonal and environmental factors. Karcıoğlu and Özer (2018) analyzed the effects of weather and lunar phase anomalies on BIST indices using ARCH-GARCH models and found that lunar phases have an effect on returns and volatility, especially during crisis periods. However, the weather effect was only found to be significant on volatility. Arı and Yüksel (2017) analyzed the effect of the day of the week using GARCH models and argued that weekly return differences in the BIST 100 index were not significant, thus suggesting that the market was weakly efficient. However, Karcıoğlu and Özer (2017) identified negative returns on Mondays and positive returns on Wednesdays, demonstrating that the days of the week and holiday anomalies influence volatility. Aytekin and Sakarya (2014) investigated whether there is a January anomaly in the Istanbul Stock Exchange and showed that many indices achieve higher returns in January compared to other months. These findings indicate that calendar anomalies should be considered in investment decisions. Küçüksille (2013) examined the effect of moon phases on the returns of the Istanbul Stock Exchange 100 Index and found no significant relationship. This result suggests that some anomalies do not have generalizable effects on market behavior.

Literature gap and contribution

The existing literature has largely examined the effects of weather variables (temperature, humidity, cloud cover, precipitation, wind, etc.) on financial markets using general and static models, revealing that these effects may vary depending on countries' economic structures, geographical characteristics, and seasonal dynamics. However, these studies do not consider the changing nature of market dynamics over time and the fact that causal relationships may vary depending on time and the direction of shocks. The current study addresses this shortcoming and contributes to the literature in several ways: First, it goes beyond the static approaches in the literature by examining the causal relationship between wind speed and BIST returns within its time-varying structure. Thus, it analyses when causality emerges and how it varies depending on the direction of shocks. Second, separately examining the effects of positive and negative wind shocks on stock market returns reveals asymmetric behavior sensitive to the direction of investor reactions. In this regard, the study tests behavioral finance theory in greater depth. Third, seasonal differences are included in the analysis. While seasonal effects are generally limited to general trends in the literature, this study demonstrates that the effect of wind varies, particularly in autumn and winter months, through seasonal decomposition. This finding suggests that the effects of climatic variables may vary in a seasonal context. Finally, it is one of the first studies to analyze the causal effect of wind speed on stock market returns in the Turkish market based on shocks that change over time and vary in direction. In this respect, it offers an innovative framework in terms of both methodological originality and contribution to the regional literature. Thus, the study fills a gap in the literature by analyzing the effect of a limited environmental variable such as wind speed on stock market returns in Turkey, a developing market, using dynamic causality tests.

DATASET AND METHODOLOGY

The study was initially designed based on wind direction and wind intensity, but no meaningful results could be obtained regarding wind direction. Therefore, the rest of the study is based on the relationship between wind speed and stock market returns and is modeled as follows. Data on average wind speed were obtained from the Turkish State Meteorological Service, and stock market index data were obtained from Borsa Istanbul. The data are daily and cover the period from 2005 to 2020. To obtain more robust results, the natural logarithm of the series was taken. Descriptive statistics of the data are included in Table 1.

A myriad of structural changes arising from economic, political, and weather-related factors can reshape the relationships between the variables studied. Therefore, a wide range of literature (Demirtaş et al., 2021; Soyu Yıldırım and Ilıkkan Özgür, 2023) emphasizes the importance of time-varying analysis methods, as the Granger causality test based on the traditional VAR model may exhibit asymptotic characteristics when the variables are integrated or cointegrated. To address this issue, Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996) propose a solution that ensures the standard asymptotic distribution of variables under the conditions specified in Equation (1). This study utilizes the bootstrap causality test developed by Hacker and Hatemi-J (2006), which is based on the Toda and Yamamoto (1995) causality test. The basic VAR(p) model with two variables is defined as follows to test for Bootstrap LR Granger causality (Balcilar et al., 2010):

Table 1. Descriptive Statistics

	Stock	Wind		Stock	Wind		Stock	Wind
Mean	65085.6	2.6207	**S. D.**	27165.	1.1687	**Prob.**	0.0000	0.0000
Med.	65970.1	2.3000	**Skew.**	-0.1507	1.5047	**Sum**	2.60E+	10472.
Max.	123556.	9.2000	**Kurt.**	2.4701	6.6182	**Sum Sq.**	2.95E+	5457.0
Min.	1034.40	0.0000	**J-B**	61.882	3687.7	**Obs.**	3996	3996

$$y_t = \theta_0 + \theta_1 y_{t-1} + \cdots + \theta_p y_{t-p} + \varepsilon_t, \quad t = 1,2, \ldots T \quad (1)$$

In the model, y_t, θ_0 are n-dimensional vectors whereas θ_p is defined as the $n \times n$ matrix of parameters obtained for the p-th lag. $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})$describes the non-singular covariance matrix $\sum$ and zero mean independent white noise process. The length of p-th lag is calculated via Akaike Information Criterion (AIC).

Toda and Yamamoto (1995) propose an extended VAR (p+d) model to test for the causality between integrated variables.

$$y_t = \theta_0 + \theta_1 y_{t-1} + \cdots + \theta_p y_{t-p} + \theta_{p+d} y_{t-p-d} + \varepsilon_t, \quad t = 1,2, \ldots T \quad (2)$$

p represents the optimal lag length while d symbolizes the maximum integration degree, in the model.

Hacker and Hatemi-J (2006), argue that in the event that a test with a distribution is undertaken via a bootstrap technique, some problems (including misleading outcomes due to the inability to ensure correct size in finite samples) might be eliminated. Hence, more reliable critical values can be obtained and deviations from estimations can be minimized. The sub-periods are defined as follows:

$$t = \tau - l + 1, \tau - l, \ldots, \tau, \tau = l, l + 1, \ldots T \quad (3)$$

In the equation, *" I "* represents the magnitude of the rolling window; therefore, a causality test is performed on each sub period in time-varying causality test. As emphasized by Brooks and Hinich (1998), a critical step in this methodology is to decide on the length of the sub period (the number of windows) (Brooks & Hinich, 1998). This study determines the number of windows as 114 by considering the methodology of Phillips, Shi, and Yu (2015) and using the formula for (0.01+1.8/√T). Then, a Hacker and Hatemi-J (2006) causality is performed for the range between the 1st and the 114th observation. This process is then repeated by removing the first observation and adding a new one observation to the sample each time, until the last observation is exhausted. It should be stated that MWALD test statistics and bootstrap critical values obtained are time-dependent. To test for the significance of these statistics, each test statistic obtained for each observation range is normalized with the 10% bootstrap critical value. The MWALD test statistics are then graphed for interpretation, and a causal relationship is found for periods where statistical values are higher than 1 (Yilanci & Bozoklu, 2014).

EMPIRICAL RESULTS

Time-Varying Symmetric Causality Test

The method employed determines whether there are changes in the stock market index based on wind speed. If there are changes, it also indicates when these changes occur. The results of the time-varying relationship between wind speed and the stock market index are displayed in Figure 1.

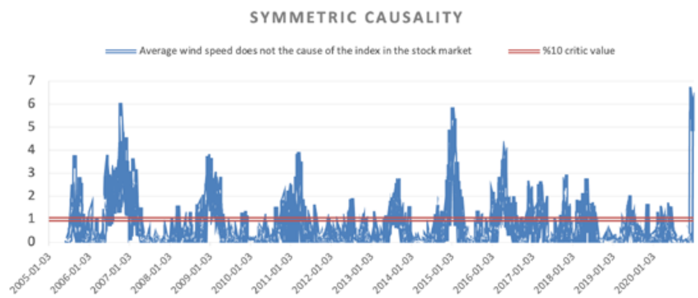

Figure 1. Time Varying Symmetric Causality Test Results

The findings have been categorized according to years and seasons. Accordingly, for the years 2005 to 2006, the observed patterns of causality are: In the summer season; in 2005, there is a causality relationship between July 25 and August 29. In 2006, the causality relationship covers a longer time period, extending from June 1 to August 31. In the autumn season, in 2005, there is a causality relationship between October 4 and 26. In 2006, the causality relationship covers a longer time period, extending from September 1 to November 30. In the winter season, in 2005, there is a causality relationship on January 16 and 17. In 2006, there is a causality relationship throughout the entire month of December. In the spring season, causality exists only in 2006. It occurred between May 22 and 31.

For the years 2007 and 2008, the pattern of causal links is as follows: In the summer season, there is no causality relationship between 2007 and 2008. In the autumn season, for the year 2007, there is no causality relationship. In 2008, the causality relationship exists between September 19 and 26, October 30 and November 18, and November 24 and 28. In the winter season, for the year 2007, there is a causality relationship over an extended period, from January 9 to February 28. In 2008, there is a causal relationship throughout the entire month of December. In the spring season, causality exists only in 2007. It occurred between March 1 and 23.

For the years 2009 and 2010, the detected causal periods are: In the summer season, similar to the period between 2007 and 2008, there is no causality relationship between 2009 and 2010. In the autumn season, there is a brief causality relationship only in the year 2010, between October 18 and November 1. In the winter season, for the year 2009, there is a causality relationship over an extended period, from January 2 to February 27. Additionally, in 2010, there is a causality relationship between December 1 to 8 and December 13 to 31. In the spring season, causality exists only in 2009. It occurred between March 2 and April 6.

For the years 2011 and 2012, the causal intervals can be summarized as follows: In the summer season, there is a causality relationship only in the year 2012, on July 5th and July 20th. In the autumn season, there is no causal relationship between 2011 and 2012. In the winter season, there is a causality relationship only in the year 2011. It occurred between January 5 and 11 and February 24 and 28. In the spring season, causality exists only in 2011. It occurred between March 1 and April 12, and April 15 and April 27. Overall, there is less causality relationship in the period between 2011 and 2012 compared to other periods, especially in the year 2011.

For the years 2013 and 2014, the identified causal events are: In the summer season, there is a causality relationship only in the year 2013. It occurred between June 21 and August 29. In the autumn season, in 2013, there is a causality relationship only between September 2 and 18. In 2014, the causality relationship covers a longer time period, occurring on September 2, and between September 12 and 17, as well as between November 6 and 28. In the winter season, there is a causality relationship only in the year 2014, throughout the entire month of December. In the spring season, there is no causality relationship.

For the years 2015 and 2016, the periods showing causality are: In the summer season, there is a causality relationship only in the year 2016, between June 1 and 7 and on July 15. In the autumn season, there is no causality relationship. In the winter season, in 2015, there is a causality relationship throughout the entire month of February. In 2016, there is a causal relationship between February 15 and 29, as well as throughout the entire month of December. In the spring season, causality exists in both periods. In 2015, it occurred on March 2 and April 9 for one day each, and between March 13 and April 3. In 2016, it occurred between March 1 and May 31.

For the years 2017 and 2018, the seasons exhibiting causality are: In the summer season, there is no causality relationship between 2017 and 2018. In the autumn season, there is a brief causality relationship only in the year 2017, between October 10 and 31. In the winter season, there is a causality relationship only in the year 2017, between January 19 and 25. In the spring season, causality exists in both 2017 and 2018. In 2017, it occurred between March 1 and April 17, and throughout the entire month of May. In 2018, it occurred between April 4 and 11, and, as in 2017, throughout the entire month of May.

For the years 2019 and 2020, the periods demonstrating causality are: In the summer season, there is a causality relationship only in the year 2019, between June 3 and 17. In the autumn season, there is no causality relationship. In the winter season, there is a causality relationship only in the year 2020, between December 10 and 31. In the spring season, causality exists only for a brief period between May 27 and 31.

Time-Varying Asymmetric Causality Test

Tests developed for causality analysis (Toda & Yamamoto, 1995; Hacker & Hatemi-J, 2006) do not differentiate between the impacts of positive and negative shocks. However, the effects of structural changes (such as wind change and climate change) can differ, hence causing deceptive outputs if one of those tests are undertaken to explain such phenomena. The lemma that the relationship between positive and negative shocks can change with the interconnections between variables is first proposed by Granger and Yoon (2002). The authors argued that economic series can be co-integrated if they jointly respond to shocks, but no such co-integration is prevalent if such response is discrete for each series. Hatemi-J (2012) develops this approach of Granger and Yoon (2002) for causality analysis. This asymmetric causality test aims to discover the embedded structure that will enable to understand the series' dynamics and improve the estimations to be made in the possible future, as it is with the Granger and Yoon (2002) co-integration analysis.

Positive and negative shocks prevalent in each variable is presented in a cumulative format in equation (4).

$$y_{1i}^{+} = \sum_{i=1}^{t} \varepsilon_{1i}^{t}, \; y_{1i}^{-} = \sum_{i=1}^{t} \varepsilon_{1i}^{-}, \; y_{2i}^{+} = \sum_{i=1}^{t} \varepsilon_{2i}^{+} \; y_{2i}^{-} = \sum_{i=1}^{t} \varepsilon_{2i}^{-} \quad (4)$$

y_{1t}^{+}, y_{1t}^{-}, y_{2t}^{+}, y_{2t}^{-} and represent positive shocks of the first variable, negative shocks of the first variable, positive shocks of the second variable and negative shocks of the second variable respectively.

This study tests the stability of the causal relationship between positive and negative shocks via using the time-variant version of the asymmetric causality test developed by Hatemi-J (2012).

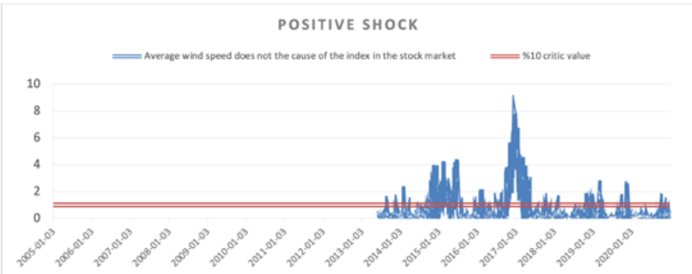

Figure 2. Time Varying Asymmetric Causality Test Results in Positive Shock

The time-varying asymmetric causality results, just like in the time-varying symmetric causality test, have been classified according to years and seasons. The asymmetric causality findings have been separated into positive and negative shock components. We begin by presenting the results corresponding to the positive shock component. These results suggest that positive shocks in average wind speed, indicative of adverse processes, may further induce positive shocks in stock returns. Consequently, it can be interpreted that an increase in average wind speed represented by positive shocks in the positive component component may lead to a decrease in stock returns. The causal results for the positive component are as follows: For the years 2014 and 2015, the positive shock component of asymmetric causality relationship is as follows: In the summer season, there is an asymmetric causality relationship only in the year 2015. It occurred between June 1 and July 6. In the autumn season, in 2014, there is an asymmetric causality relationship between October 10 and November 11, and around November 17. In the winter season, in 2014, there is an asymmetric causality relationship on February 7 and throughout the entire month of December. Additionally, in 2015, there is a causality relationship between January 1 and 9, and between January 20 and February 27.

For the years 2016 and 2017, the positive shock component of asymmetric causality relationship is as follows: In the summer season, there is an asymmetric causality relationship only in the year 2016, between August 2 and 8. In the autumn season, only in 2016, there is a long-term asymmetric causality relationship between October 6 and November 30. In the winter season, there is a causality relationship in both periods. However, in 2016, there is a causality relationship on December 1 and February 28 for one day each. In the spring season, causality exists only in the year 2017, between March 1 and May 8.

For the years 2018 and 2019, the positive shock component of asymmetric causality relationship is as follows: In the summer season, no asymmetric causality is observed for the positive component in 2018 and 2019. In the autumn season, there is a causality relationship in both periods. However, in 2018, there is a causality relationship on October 30 for one day only. In 2019, there is a causality relationship between November 19 and 26 for a short period. In the winter season, there is no asymmetric causality relationship for the positive component in the years 2018 and 2019. In the spring season, there is a causality relationship only in the year 2019, between March 1 and 25.

In summary, positive shocks tend to cluster in the autumn and winter seasons, whereas the summer period exhibits the least causality.

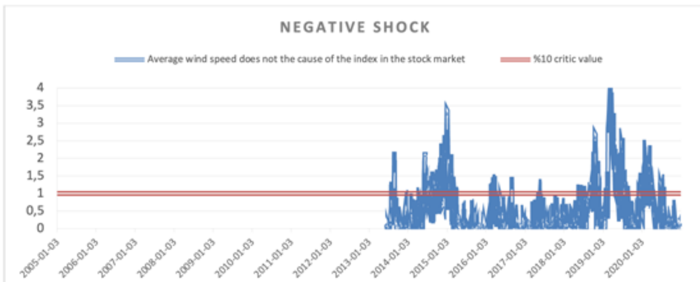

Figure 3. Time Varying Asymmetric Causality Test Results in Negative Shock

The negative shock component was first observed in 2013. These findings suggest that negative shocks in average wind speed, indicative of positive processes, can potentially trigger corresponding negative shocks in stock returns. Consequently, it can be interpreted that a decrease in average wind speed due to negative shocks in the negative component may lead to an increase in stock returns. The causal results for the negative component are as follows: For the years 2013 and 2014, the negative shock component of asymmetric causality relationship is as follows: In the summer season, there is an asymmetric causality relationship in both years. In 2013, it occurred between June 26 and 29. In 2014, it occurred between June 4 and July 9, and on August 21 for one day. In the autumn season, there is a causality relationship only in 2014, between September 3 and 24, between September 29 and October 9, between October 15 and November 4, and between November 11 and 21. During the 2014 winter season (spanning December 2014 to February 2015), a causality relationship occurs throughout December. In the spring season, there is no causality relationship for the negative component of the asymmetric test between 2013 and 2014.

For the years 2015 and 2016, the negative shock component of asymmetric causality relationship is as follows: In the summer season, there is no causality relationship for the negative component of the asymmetric test between 2015 and 2016. In the autumn season, there is no causality relationship for the negative component of the asymmetric test between 2015 and 2016. In the winter season, there is a causal relationship only in 2015, between January 2 and February 16. In the spring season, causality exists only in the year 2016, between March 16 and 25.

For the years 2018 and 2019, the negative shock component of asymmetric causality relationship is as follows: In the summer season, there is a causality relationship in both years. In 2018, the asymmetric causality relationship is presented on August 31 for one day. In 2019, it occurs between June 12 and July 23. In the autumn season, there is a causality relationship in both years. However, in 2018, it occurs only on October 30 for one day. In 2019, it occurs between November 19 and 26 for a short period. In the winter season, there is a causality relationship only in the year 2019. In 2019, it occurs between January 29 and February 4, between February 14 and 28, and for one day each on December 5, 12, and 20. In the spring season, there is a causality relationship only in the year 2019, between March 1 and May 7, and between May 16 and 23.

For the year 2020, the negative shock component of the asymmetric causality relationship is as follows: In the summer season, there is a causality relationship in 2020, between June 26 and July 6. In the autumn season, there is no causality relationship for the negative component of the asymmetric test in 2020. In the winter season, there is a causality relationship in 2020, between January 15 and February 28. In the spring season, it occurs for a long period between March 2 and May 9 in 2020.

Overall, it can be observed that the causality relationship in the negative shock component tends to concentrate during the winter season. In contrast, the autumn season has less intensity of causality. The spring and summer seasons, on the other hand, have similar intensities, which are higher than the autumn season.

The findings of the time-varying symmetric analysis, along with wind speeds, have been combined to create a graph. This graph includes both the analysis results and the dates on which wind speeds occurred. In this way, the relationship between wind speed and stock returns can be more clearly visualized. These findings are visualized in Figure 4.

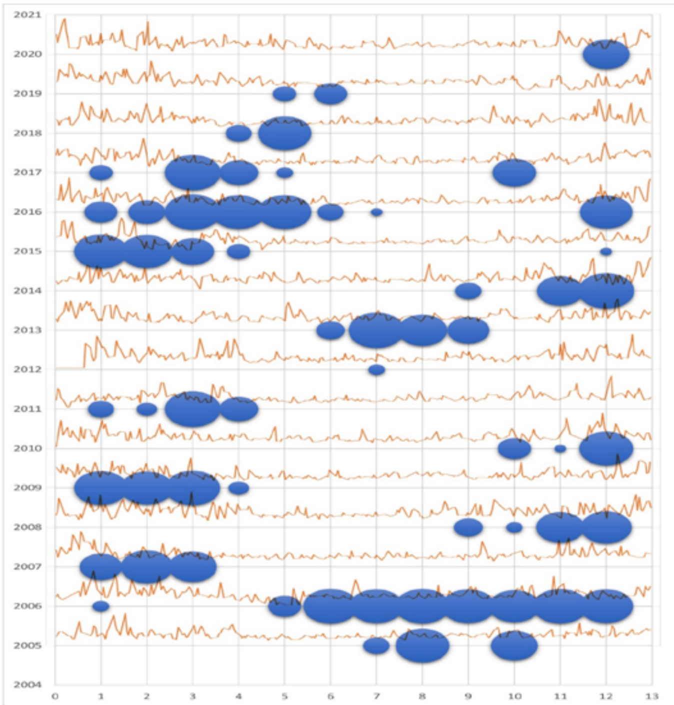

Figure 4: Periods of Causality with Average Wind Speed

CONCLUSION

This study examines the effect of wind speed on stock market returns by conducting time-varying tests for both symmetric and asymmetric causality. The findings of these tests are then presented according to specific years and seasons. The findings from the symmetric test show that the effect of wind speed on stock returns is particularly notable in specific years and seasons. According to the findings of the asymmetric causality test, positive wind shocks may lead to a decrease in stock market returns, especially in autumn and winter, while negative wind shocks may lead to an increase in market returns, especially in winter. A positive wind shock—defined as a sudden increase in wind speed—can be interpreted as a signal that weather conditions will deteriorate (e.g., storm risk, transportation disruptions). This situation may increase risk perception among investors, leading to a decline in stock returns. In contrast, a negative wind shock – a sudden decrease in wind speed – may be interpreted as an improvement in weather conditions or at least greater stability. This could boost investor confidence, resulting in an increase in market returns. In addition, a graph was created by combining the findings of the time-varying symmetric analysis with wind speeds, thus strengthening the visualization of the relationship between wind speed and stock market returns. In general, there is a robust causal relationship between the duration of the causal relationship and average wind speed. However, this relationship weakens under exceptional conditions. Turkey experienced significant events such as the Gezi Park Protests, the Ergenekon and Balyoz Cases, and the biggest corruption scandal in the history of the Republic of Turkey during 2012, 2013, and 2014. These events coincided with periods of declining strength of the causal relationship. In terms of external relations, there was a simultaneous crisis involving Syria and an ongoing problem with refugees. The Istanbul Stock Exchange experienced a notable impact from wind speed variations during these periods. Correspondingly, the causal relationship between wind speed and stock returns weakened during the pandemic. These events, whether internal or external, can be considered as potential reasons contributing to the decline in this relationship.

The findings suggest that variations in wind speed may exert effects on stock markets that are dependent on both time and season. In particular, it has been found that positive and negative shocks in wind speed asymmetrically affect stock market returns, especially in autumn and winter. These results offer important insights for both policymakers and investors. In this context, monitoring meteorological indicators alongside economic indicators can assist public authorities in predicting investor behavior. Additionally, considering that the impact of climatic factors on markets weakens during extraordinary periods (e.g., political crises, pandemics), economic policies implemented during such periods should be designed with a more comprehensive approach.

In terms of recommendations for investors, climate data have emerged as a factor to be considered in stock investments, particularly for short-term positions. Findings that positive or negative shocks in wind speed during autumn and winter months can affect market behavior may enable investors to develop seasonal strategies. However, considering that this relationship weakens during extraordinary socio-political periods, it is important to evaluate not only meteorological data but also macroeconomic and geopolitical developments when making investment decisions. As a result, this comprehensive analysis is expected to serve as a valuable tool for understanding the impact of wind speed on financial markets and developing more accurate models for future forecasts.

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