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Does Geopolitical Risk and Investors' Sentiment Matter for Turkish Stock Returns?

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ABSTRACT

The relationship among geopolitical risk, investor sentiment and stock returns is an important topic. This article investigates the effects of geopolitical risk and the Consumer Confidence Index for Turkish stocks returns over a period from the start of 2004 to the end of 2017. This study uses monthly data for stock returns (BIST100) and the GPR index, a constructed monthly geopolitical risk index (Caldara and Iacoviello, 2018). The empirical analysis is founded on the Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MGARCH) method, specifically the DCC-GARCH and BEKK-GARCH models. The results show that geopolitical risk and investor sentiment have a negative effect, essentially on BIST100 returns and volatility.

ملخص

تعتبر العلاقة بين المخاطر الجيوسياسية وشعور المستثمرين وعائدات الأسهم موضوعا هاما. وهذا المقال، يتحرى آثار المخاطر الجيوسياسية ومؤشر ثقة المستهلك لعائدات الأسهم التركية على مدى فترة تمتد من بداية عام 2004 حتى نهاية عام 2017. وتستخدم هذه الدراسة البيانات الشهرية لعائدات الأسهم (BIST100) ومؤشر المخاطر الجيوسياسية، الذي يعتبر مؤشرا شهريا للمخاطر الجيوسياسية (Caldara and Iacoviello, 2018). ويستند التحليل التجريبي إلى نموذج التباين الذاتي

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الشرطي المعمم المتغاير (MGARCH)، وعلى وجه التحديد نموذجي الارتباط الدينامي المشروط-التباين الذاتي الشرطي المعمم (DCC-GARCH) وبابا، إنجل، كرافت، كرونر-التباين الذاتي الشرطي المعمم (BEKK-GARCH). وتبين النتائج أن للمخاطر الجيوسياسية وشعور المستثمرين أثرا سلبيا، أساسا على عائدات الأسهم (BIST100) وتقلباتها.

ABSTRAITE

La relation entre le risque géopolitique, le sentiment des investisseurs et les rendements boursiers est un sujet important. Cet article étudie les effets du risque géopolitique et de l'indice de confiance des consommateurs sur les rendements des actions turques sur une période allant du début de 2004 à la fin de 2017. Cette étude utilise les données mensuelles des rendements boursiers (BIST100) et l'indice GPR, un indice de risque géopolitique mensuel construit (Caldara et Iacoviello, 2018). L'analyse empirique est fondée sur la méthode MGARCH (Multivariate Generalized Autoregressive Conditional Heteroskedasticity), plus précisément sur les modèles DCC-GARCH et BEKK-GARCH. Les résultats montrent que le risque géopolitique et le sentiment des investisseurs ont un effet négatif, essentiellement sur les rendements et la volatilité du BIST100.

Keywords: Geopolitical risk index; Investors' sentiment; Turkish stock returns; Multivariate GARCH models, BEKK/DCC form

JEL Classification: H56; G1; G15

1. Introduction

Many studies have focused on stock markets whose fluctuations are affected by economic factors that can also be extremely sensitive to political events (Pástor and Veronesi, 2013; Hudson and Urquhart, 2016). Political events, whether national or international, can cause disturbance on the general economy, financial markets and more particularly stock markets. This disturbance can influence the sentiment of economic agents and lead to a financial crisis (Bialkowski et al., 2008; Wolfers and Zitzewitz, 2009). Nevertheless, an uncertain environment can be brought about by political instability caused by, for example, elections, political uncertainty, government changes, and civil strife, as well as terrorism has been grafted onto a structural weakness in the economy or can lead to countless economic problems. This in turn can lead to an increase in the rate of return that investors demand (Guidolin and La Ferrara, 2010; Drakos and Kallandranis, 2015, Islam et al., 2019). Similarly, geopolitical friction, international tension, and armed conflict between states give rise to a significant level of risk and uncertainty that can damage global markets (Zussman et al., 2008, Abdalla et al., 2017).

Perhaps the best-known example of a country affected by geopolitical events is Turkey. Domestically, we can point to the political crisis that started in July 2008 following the court's rejection of a request to close down the AKP on the basis that it had become "a center of anti-secular activities." Following the largest protests in the history of the Turkish Republic in the summer of 2013, the AKP won the subsequent elections. Finally, the attempted coup of July 2016 was an important internal event for Turkey. Externally, we can highlight the political instability in Lebanon, the start of the Syrian Civil War in 2011, and Russia's entry into Syria in September 2015.

The field of behavioral finance has experienced significant expansion and development in recent decades. Indeed this field encompasses both concepts of psychology and finance. It aims to build a more detailed model of investor behavior. The advantage of behavioral finance is that it emphasizes the functioning of the human mind and the psychological profile of the investor. Lee, Jiang and Indro (2002) examined a sample for the period 1973–1995 and found that investor behavior leads to variability in future returns. In addition, Baker et al. (2012) confirmed that investor sentiment helps predict returns because it is an important factor in the volatility of international markets. In a study based on all CAC firms during the 2003–2013 period, Ben Aissia (2014) examined the effects of investor sentiment on stock market returns. The impact of sentiment is more pronounced when valuing real estate stocks. However, Haiqi Li and Sung Y. Park (2017) examined the effect of investor sentiment on the predictability of stock returns using the Consumer Confidence Index. Their study found that the price of a security cannot be disconnected from any reality positively influenced by investor sentiment during times of boom and deteriorate during times of recession.

The current paper contributes to the literature in some novel areas. First, our study complements the existing behavioral literature. Second, this research is of particular interest because it considers both geopolitical risk and investor sentiment and their impacts on stocks returns, because previous studies have not shed any light on the relationships that exist among geopolitical risk, investor sentiment, and stock returns. Third, this research will have implications for the stock markets, a stabilizer to investment strategies exposed to stock volatility and its outlook can help investors control their feelings and control the dangers ahead.

In this paper, we investigate the impact of geopolitical risk and the consumer confidence index on stock market returns based on monthly data for Turkey, namely the BIST100 index, the GPR index, and the Consumer Confidence Index as a proxy for investor sentiment. The period of this empirical investigation covers the start of 2004 to the end of 2017. The GPR index is inserted into a multivariate Generalized Autoregressive Conditional Heterosedasticity (MGARCH) model, specifically of the DCC-GARCH and BEKK-GARCH forms. We employ an unrestricted vector autoregressive GARCH model here for two main reasons: First, it presents a causal analysis and modeling between two or more variables without explicitly granting a specific direction. Second, the events studied in market finance are, for the most part, the result of a rational and voluntary decision by investors. However, the standard techniques implemented in event analysis do not take account of variances varying over time; this particular aspect of the event suggests that modeling conditional variances and covariance is an appropriate approach.

Our results reveal that in terms of the profitability and variability of the stock market indices, it does not convey any superiority over the consumer confidence index (CCI) which enjoys more influence by the

GPR index. Moreover, the extent of volatility transmission among the CCI, BIST100, and geopolitical risk indexes is very interesting, empirical results show that past geopolitical proximity plays a crucial role in explaining the variation in volatility over time of BIST100 in Turkey; this is useful for forecasting future price fluctuations.
The remainder of this article is organized as follows: Section 2 reviews the literature on the relationship between geopolitical risk, stock markets, and investor sentiment, while Section 3 details the data and methodology used in this analysis. Section 4 then discusses the empirical results before Section 5 concludes the paper.

2. Literature review

The relationships that exist between geopolitical risk, stock markets, and investor sentiment have been extensively, albeit separately, examined in some previous literature, with them reporting mixed results using different techniques and models. Among these, we can look to the study of Diamonte, Liew, and Stevens (1996), who demonstrated that political risk affects stock returns more in emerging markets than in developed markets. However, contrasting results were reported in the study of Clark (1997), who developed a model for measuring the implications of political risk for foreign direct investment. In addition, Clark and Tunaru (2001) created a new model for measuring the effect of political risk on portfolio investments. Meanwhile, based on a sample of 22 international companies in Malaysia, Noordin, Harjitoand, and Hazir (2006) tried to identify political risk assessment strategies. They found that most preferred a "good citizen" policy as a means to decrease political risk. Yapraklı and Gungor (2007), meanwhile, provided evidence of causality between political risk and the BIST100 index, but they did not manage to repeat this with financial risk. In their study, Sanlisoy and Kök (2010) found an inverse relationship between economic growth and political issues.

Baek and Qian (2011), meanwhile, demonstrated how political risk has had a very significant effect on foreign direct investment since the

September 11 attacks of 2001. Using a GARCH approach, Kollias et al. (2011) studied the effects that the Madrid train bombings in March 2004 and the London terrorist attacks in July 2005 had on the financial markets. They found that the London Stock Exchange (LSE) experienced some serious effects following the bombings, while the Spanish market went through significant negative effects following the Madrid bombings, with the volatility in the Spanish market being much higher than that of the London market. For their part, Peleg, Regens, Gunter, and Jaffe (2011) looked at Israeli markets over the 2000–2006 period and observed an exceptional new behavior, specifically a "normalization" of markets and investors to acts of terrorism. On the other hand, Berkman, Jacobsen and Lee (2011), in their work, counted the number of international crises to create a disaster risk variable, and they found this may be an important factor that ultimately decreases stock prices.

Ahmed and Mustafa (2019), seeks to establish the close relationship between macroeconomic variables (the change in the exchange rate, the inflation rate, the interest rate and the growth of industrial production) and stock returns for the case of Pakistan. By applying the ARDL approach and cointegration, the results show a significant effect between stock market returns and macroeconomic indicators on the one hand and the existence of a cointegration relationship between the study variables. This analysis can help investors make optimal decisions about their investments.

Çam (2014), meanwhile, examined the relationship in Turkey between political risk and the trade in BIST100 companies, with the results revealing a strong correlation between political risk in Turkey and these companies' performances. In their study of Turkey, Kaya et al. (2015) support the existence of a long-term negative relationship between BIST100 returns and political risk. Samet Günay (2016), meanwhile, analyzed the potential risks arising from internal political events and the duration of their effects on the Turkish stock market over the 2001–2014 period. The results illustrated how BIST100 returns are proportionally influenced by political events.

Studies that focus on the relationships that exist between geopolitical risk, investor sentiment, and stock returns are very limited. To examine the relationship between investor sentiment and stock returns, we looked at various indicators that could be used. For example, Brown and Cliff (2004) examined the effect of investor sentiment on stock returns using various measures, demonstrating that measures of investor sentiment affect big and small stock returns equally. Lemmon and Portniaguina (2006), meanwhile, applied the commonly used Consumer Confidence Index (CCI) in an attempt to measure investor sentiment and showed that consumer confidence can predict stock returns, especially for small stocks. Based on monthly Turkish data between July 1997 and June 2006, Canbas and Kandir (2006) tested the impact of investor sentiment on international stock markets, with their results revealing that investor sentiment affects Turkish stock returns.

In addition, Schmeling (2009) showed firstly that an investor sentiment indicator could be used to predict the variability of the stock markets and secondly that this effect is more pronounced in a country where there is less freedom to move capital across national borders. Guner (2009), meanwhile, showed that 10% of firms listed on the Turkish stock exchange were not influenced by investor sentiment. However, Baker et al. (2012) found that financial markets can be influenced by investor confidence indexes, both from inside and outside the country, with foreign investors contributing more due to the contagion effect through capital flows. Meanwhile, Chung, Hung, and Yeh (2012) showed that in times of economic recession, it is difficult to make predictions, unlike in times of expansion.

In addition, Mustafa and Hamid (2013) used the monthly Turkish Consumer Confidence Index over the 2004–2010 period to study the influence of individual Turkish investors' sentiment on the Istanbul Stock Exchange (ISE) and thus establish whether stock returns, investor sentiment, and volatility in Turkey are related. Their results suggest that the behavior of individual investors has a great influence on stock returns, with feelings of optimism contributing to developing positive expectations and reducing the volatility in stock market returns.

Ahmed (2020), meanwhile, proposed exploring the effects of investor sentiment on stock market performance and found that investor sentiment tends to positively affect both types of markets, albeit only in the short term. The results also highlight how the behavior of individual investors can influence on the future trajectory of asset prices more in emerging countries than in developed countries.

In conclusion, the literature as a whole would seem to suggest that geopolitical risk and the Consumer Confidence Index play a considerable role in investment decisions, so they have some consequences for financial markets, especially stock markets. Indeed, most studies confirm the negative effect of poor investor sentiment on stocks returns.

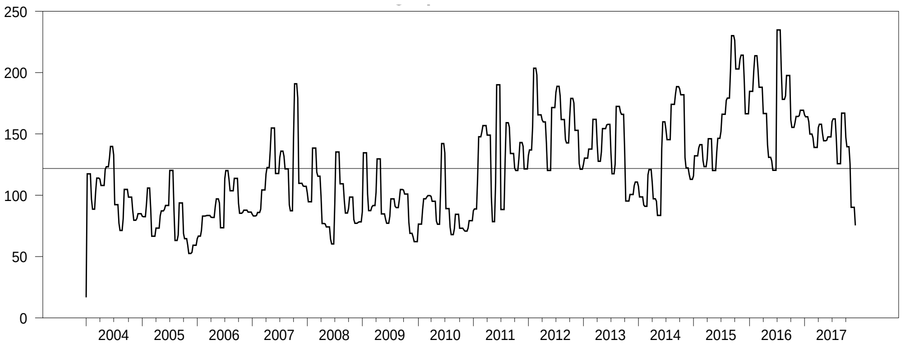
3. Data and methodology

Geopolitical risk is defined as the "risk associated with wars, terrorist acts, and tensions between states that affect the normal and peaceful course of international relations" (Caldara & Iacoviello (2018). This definition, however, excludes some other geopolitical phenomena like major economic crises, significant political events, climate change, and civil unrest. The geopolitical risk can be measured through two principal indexes proposed by Caldara and Iacoviello (2018), [4] namely the Geopolitical Threats (GPT) index—which considers geopolitical threats, nuclear threats, the threat of war, and terrorist threats—and the geopolitical acts (GPA) index, which considers acts of war and terrorism.

The GPR index constructed by Caldara and Iacoviello (2018) has the advantage that it offers the opportunity to move beyond examining how specific events affect markets and the economy in general (Frey and Kucher, 2000; Kollias, 2013; Hudson and Urquhart, 2016).

[4] Available at https://www2.bc.edu/matteo-iacoviello/gpr_files/GPR_PAPER.pdf

Figure1: Turkish geopolitical risk index



Source: Authors' results

The GPR is a monthly index that quantifies the risk associated with, and produced by, events such as tension and friction between states, confrontation, armed conflict and war, and acts of terrorism. As shown in Fig. 1, the Turkish GPR index is characterized by an oscillation with peaks being associated with various events in the region. For instance, focusing on the origin of these events, the GPR index can be derived by counting the prevalence of words related to geopolitical tension in leading international newspapers (Caldara and Iacoviello, 2018).

A remarkable rise in the GPR index between 2007 and 2008 can be explained by the subprime crisis. Furthermore, the instability of the GPR index from 2011 was triggered by the events of the Arab Spring in Tunisia, Yemen, Libya, Egypt, and Syria. Later in April 2012, the Turkish government reported a record number of Syrian refugees, which increased the level of the GPR index, as can be seen in Fig. 1. The GPR index also elevated during the 2015–2017 period. This can be explained through several reasons, including Russia's military intervention in the Syrian Civil War, the purging of *Daech* (IS/ISIS) from Iraq, and the political disturbance in Lebanon related to *Hezbollah*. Finally, the GPR index reached its maximum value in July 2016, which corresponds to the failed coup attempt that sought to take over Turkey's state institutions.

The risk generated by instability and uncertainty is transmitted to investor sentiment, financial markets, and the wider economy (Zussman et al., 2008; Kollias, 2013; Drakos and Kallandranis, 2015; Wang, 2020).

This article focuses on the role of the GPR index and the Consumer Confidence Index (CCI) as a proxy for investor sentiment and their influence on Turkish stock returns. In order to perform the empirical analyses, we chose the multivariate GARCH (MGARCH) model and more precisely widely known as the BEKK-GARCH [5] model (Engle and Kroner, 1995), and the Dynamic Conditional Correlation (DCC-GARCH) model of Engle (2002).

Moreover, we show that this model is a popular and tools to effectively model and analyze a multivariate time series. In addition, multivariate GARCH models identify equations for how the variance-covariance moves over time. In addition, DCC-GARCH and BEKK-GARCH offer a way to digitally measure the risk faced by financial institutions and individual investors. The multivariate GARCH approach is also flexible enough to modulate the dynamics of the conditional variance and covariance. What is more, the multivariate BEKK and DCC models are the twofold most usually used MGARCH models. For the above reasons, we believe that the above-mentioned multivariate GARCH models are naturally suited to our research aims.

Finally, in order to observe the impact of investor sentiment and geopolitical events, as determined more accurately by the GPR index, on Turkish stocks returns, our empirical data is based on monthly observations for the GPR index, the Consumer Confidence Index (CCI), and the BIST100 index. This study covers a period from January 2004 to December 2017. A VAR-GARCH model was used to capture the interdependencies among the GPR, BIST100, and CCI taking into

[5] The BEKK part refers to a specific parameterization of the multivariate GARCH model developed by Engle and Kroner (1995).

account the cross effects of yield as well as volatility in the following equations.

We define trivariate GARCH (1, 1) as:

$$\begin{cases} X_t = \gamma + \delta \sum_{i=1}^{p} X_{t-1} + \varepsilon_t \\ \varepsilon_t = H_t^{1/2} \eta_t \end{cases} \tag{1}$$

Where $X_t \left(BIST\,100_t, CCI_t, GPR_t \right)$ represents the returns (in real terms) of the BIST100, investor sentiment, and the stock GPR index, respectively.

In 1995, Engle and Kroner proposed the BEKK-GARCH(1, 1) model to give the advantage of parsimony and address the difficulty with VECH in that its name is taken by the vectorized representation of the model. So, to know how the variance-covariance moves over time, a multivariate GARCH model is used, specifically the one proposed in 1995 by Baba, Engle, Kraft, and Kroner, which is where the BEKK part of the model's name derives from. In our case, the joint process governing the three variables is modeled with the trivariate Vector Autoregressive (VAR) unrestricted BEKK-GARCH (1, 1) model with the introduction of the geopolitical risk index in the construction of the mean, variance, and covariance matrices. More specifically, Eq. (1) shows the form for the conditional mean.

We recognized the lag length, named *p*, by applying the Akaike (AIC) criterion. The residual vector $\varepsilon = \left(\varepsilon_1, \varepsilon_2, \varepsilon_3 \right)$ is trivariate and generalized distributed with $\varepsilon_t / \Phi_{t-1} \sim GED\left(0, \mathrm{H}_t \right)$, while the corresponding conditional variance covariance matrix is defined as:

$$\mathrm{H}_t = \begin{bmatrix} h_{11t} h_{12t} h_{13t} \\ h_{21t} h_{22t} h_{23t} \\ h_{31t} h_{32t} h_{33t} \end{bmatrix}$$

Such that the second moment is present in the following equation:

$$\mathrm{H_t} = \mathrm{C_0 C_0'} + \mathrm{A'}\varepsilon_{\mathrm{t-1}}\varepsilon_{t-1}'\mathrm{A} + \mathrm{B'H_{t-1}B} \tag{2}$$

The developed form of equation (2) is then presented as follows:

$$\mathrm{H_t} = \begin{pmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32} & c_{33} \end{pmatrix} \begin{pmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32} & c_{33} \end{pmatrix}' + \begin{pmatrix} \alpha_{11}\alpha_{12}\alpha_{13} \\ \alpha_{21}\alpha_{22}\alpha_{23} \\ \alpha_{31}\alpha_{32}\alpha_{33} \end{pmatrix}' \varepsilon_{\mathrm{t-1}}\varepsilon_{t-1}' \begin{pmatrix} \alpha_{11}\alpha_{12}\alpha_{13} \\ \alpha_{21}\alpha_{22}\alpha_{23} \\ \alpha_{31}\alpha_{32}\alpha_{33} \end{pmatrix} + \begin{pmatrix} \beta_{11}\beta_{12}\beta_{13} \\ \beta_{21}\beta_{22}\beta_{23} \\ \beta_{31}\beta_{32}\beta_{33} \end{pmatrix}' \mathrm{H_{t-1}} \begin{pmatrix} \beta_{11}\beta_{12}\beta_{13} \\ \beta_{21}\beta_{22}\beta_{23} \\ \beta_{31}\beta_{32}\beta_{33} \end{pmatrix} \tag{3}$$

In a single equation, the BEKK-GARCH model may be presented as follows:

$$\begin{aligned} h_{11t} = {} & C_{11}^2 + \alpha_{11}^2\varepsilon_{1,t-1}^2 + \alpha_{21}^2\varepsilon_{2,t-1}^2 + \alpha_{31}^2\varepsilon_{3,t-1}^2 + 2\alpha_{11}\alpha_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 2\alpha_{11}\alpha_{31}\varepsilon_{1,t-1}\varepsilon_{3,t-1} \\ & + 2\alpha_{31}\alpha_{21}\varepsilon_{2,t-1}\varepsilon_{3,t-1} + h_{11,t-1}(\beta_{11}^2 + \beta_{12}^2 + \beta_{13}^2) + h_{21,t-1}(\beta_{11}\beta_{21} + \beta_{12}\beta_{22} + \beta_{13}\beta_{23}) + \\ & h_{31,t-1}(\beta_{11}\beta_{31} + \beta_{12}\beta_{32} + \beta_{13}\beta_{33}) \end{aligned} \tag{4}$$

$$\begin{aligned} h_{22t} = {} & c_{21}^2 + c_{22}^2 + \alpha_{12}^2\varepsilon_{1,t-1}^2 + 2\alpha_{12}\alpha_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \alpha_{22}^2\varepsilon_{2,t-1}^2 + 2\alpha_{12}\alpha_{32}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 2\alpha_{22}\alpha_{32}\varepsilon_{2,t-1}\varepsilon_{3,t-1} + \alpha_{32}^2\varepsilon_{3,t-1}^2 \\ & + h_{22,t-1}(\beta_{21}^2 + \beta_{22}^2 + \beta_{23}^2) + h_{12,t-1}(\beta_{21}\beta_{11} + \beta_{22}\beta_{12} + \beta_{23}\beta_{13}) + h_{32,t-1}(\beta_{21}\beta_{31} + \beta_{22}\beta_{32} + \beta_{23}\beta_{33}) \end{aligned} \tag{5}$$

$$\begin{aligned} h_{33t} = {} & c_{31}^2 + c_{32}^2 + c_{33}^2 + \alpha_{13}^2\varepsilon_{1,t-1}^2 + \alpha_{23}^2\varepsilon_{2,t-1}^2 + \alpha_{33}^2\varepsilon_{3,t-1}^2 + 2\alpha_{13}\alpha_{23}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 2\alpha_{13}\alpha_{33}\varepsilon_{1,t-1}\varepsilon_{3,t-1} \\ & + 2\alpha_{23}\alpha_{33}\varepsilon_{2,t-1}\varepsilon_{3,t-1}h_{33,t-1}(\beta_{31}^2 + \beta_{32}^2 + \beta_{33}^2) + h_{13,t-1}(\beta_{31}\beta_{11} + \beta_{32}\beta_{12} + \beta_{33}\beta_{13}) \\ & + h_{23,t-1}(\beta_{31}\beta_{21} + \beta_{32}\beta_{22} + \beta_{33}\beta_{23}) \end{aligned} \tag{6}$$

$$\begin{aligned} h_{12t} = {} & c_{11}c_{21} + \alpha_{12}\alpha_{11}\varepsilon_{1,t-1}^2 + \alpha_{22}\alpha_{21}\varepsilon_{2,t-1}^2 + \alpha_{32}\alpha_{31}\varepsilon_{3,t-1}^2 + (\alpha_{12}\alpha_{21} + \alpha_{22}\alpha_{11})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \\ & (\alpha_{12}\alpha_{31} + \alpha_{32}\alpha_{11})\varepsilon_{1,t-1}\varepsilon_{3,t-1} + (\alpha_{22}\alpha_{31} + \alpha_{32}\alpha_{21})\varepsilon_{2,t-1}\varepsilon_{3,t-1} + h_{12,t-1}(\beta_{11}^2 + \beta_{12}^2 + \beta_{13}^2) + \\ & h_{22,t-1}(\beta_{11}\beta_{21} + \beta_{12}\beta_{22} + \beta_{13}\beta_{23}) + h_{32,t-1}(\beta_{11}\beta_{31} + \beta_{12}\beta_{32} + \beta_{13}\beta_{33}) \end{aligned} \tag{7}$$

$$
\begin{aligned}
h_{13t} &= c_{11}c_{31} + \alpha_{13}\alpha_{11}\varepsilon_{1,t-1}^{2} + \alpha_{23}\alpha_{21}\varepsilon_{2,t-1}^{2} + \alpha_{33}\alpha_{31}\varepsilon_{3,t-1}^{2} + (\alpha_{13}\alpha_{21} + \alpha_{23}\alpha_{11})\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\
&+ (\alpha_{13}\alpha_{31} + \alpha_{33}\alpha_{11})\varepsilon_{1,t-1}\varepsilon_{3,t-1} + (\alpha_{23}\alpha_{31} + \alpha_{33}\alpha_{21})\varepsilon_{2,t-1}\varepsilon_{3,t-1} + \beta_{13}\beta_{11}h_{11,t-1} + \beta_{23}\beta_{21}h_{22,t-1} \\
&+ \beta_{33}\beta_{31}h_{33,t-1} + h_{12,t-1}(\beta_{13}\beta_{21} + \beta_{23}\beta_{11}) + h_{13,t-1}(\beta_{13}\beta_{31} + \beta_{33}\beta_{11}) + h_{23,t-1}(\beta_{23}\beta_{31} + \beta_{21}\beta_{33})
\end{aligned} \tag{8}
$$

$$
\begin{aligned}
h_{23t} &= c_{21}c_{31} + c_{22}c_{32} + \alpha_{13}\alpha_{12}\varepsilon_{1,t-1}^{2} + \alpha_{23}\alpha_{22}\varepsilon_{2,t-1}^{2} + \alpha_{33}\alpha_{32}\varepsilon_{3,t-1}^{2} + (\alpha_{13}\alpha_{22} + \alpha_{23}\alpha_{12})\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\
&+ (\alpha_{13}\alpha_{32} + \alpha_{33}\alpha_{12})\varepsilon_{1,t-1}\varepsilon_{3,t-1} + (\alpha_{23}\alpha_{32} + \alpha_{33}\alpha_{22})\varepsilon_{2,t-1}\varepsilon_{3,t-1} + \beta_{13}\beta_{12}h_{11,t-1} + \beta_{23}\beta_{22}h_{22,t-1} \\
&+ \beta_{33}\beta_{32}h_{33,t-1} + h_{12,t-1}(\beta_{13}\beta_{22} + \beta_{23}\beta_{12}) + h_{13,t-1}(\beta_{13}\beta_{32} + \beta_{33}\beta_{12}) + h_{32,t-1}(\beta_{33}\beta_{22} + \beta_{23}\beta_{32})
\end{aligned} \tag{9}
$$

We used the maximum likelihood to jointly estimate the parameters of the mean and variance equations.

Engle (2002) proposed the Dynamic Conditional Correlation model. The form of Engle's DCC equation spelled this manner:

$$\mathrm{H}_{\mathrm{t}} = D_t P_t D_t \tag{10}$$

$$D_t = dig\left(h_{1t}^{1/2}, h_{2t}^{1/2}, h_{3t}^{1/2}\right) \tag{11}$$

Where each h_{it} is described by a univariate GARCH model,

Where

$$P_t = dig\left(q_{11t}^{1/2}, q_{22t}^{1/2}, q_{33t}^{1/2}\right) Q_t dig\left(q_{11t}^{1/2}, q_{22t}^{1/2}, q_{33t}^{1/2}\right), \tag{12}$$

and $Q_t = \left(q_{ijt}\right)$ is the 3*3 symmetric positive definite matrix with the form:

$$Q_t = \left(1 - \alpha - \beta\right)\overline{Q} + \alpha\eta_{t-1}\eta_{t-1}' + \beta Q_{t-1} \tag{13}$$

Here, $\eta_{it} = \varepsilon_{it} / \sqrt{h_{iit}}$ and $\left(1 - \alpha - \beta\right)$ are non-negative scalars where $\alpha + \beta \prec 1$ and $\overline{Q}$ is the 3×3 unconditional variance matrix of standardized errors η_{t}.

4. Empirical results

As mentioned above, we are interested in the relationship between the Consumer Confidence Index, the GPR index, and stock market returns. Our variables, such as the CCI, BIST100 returns, and the GPR index are I(1) processes. Table 1 summarizes their descriptive statistics. As can be seen, all variables are positive and statistically significant. In terms of volatility, the GPR index’s volatility is greater than that of the CCI or BIST100 returns.

Table 1: Descriptive Statistics

Source: Authors' results. Note: (***), (**) and (*) denote significance at 1% and 5% and 10%, respectively.

	observations	**Sample mean**	**t-statistic (p-value)**	**Std. dev.**	**Skewness**	**Kurtosis (excess)**	**Jarque-Bera**	**Ljung-box test Q(16) p-value**	**ARCH(16) LM Test p-value**
CCI	168	83.060	82.719	13.014	0.325	1.990	10.099	156.06	183.00
			0.000				<006***	<001***	<000***
BIST100_Returns	168	0.0017	0.659	0.033	-0.532	4.021	15.255	16.830	62.82
			0.000***				<000***	<007***	<000***
GPR _ Index	168	121.63	39.541	39.87	0.515	2.52	9.02	69.859	1.97
			0.501				<001***	<000***	<004***

When looking at Table 1, we note how the degree of skewness is smaller for BIST100 returns than it is for the CCI or GPR index. In addition, the Jarque–Bera values are high and statistically significant for three series, confirming rejection of the null hypothesis of normality. Furthermore, applying the ARCH test to detect heteroskedasiticity problems provides strong evidence of the ARCH effect in all series. In addition, the distribution of these variables is fat-tailed because excess kurtosis is superior to zero. As a result, adopting the VAR (p)-BEKK-GARCH and VAR-DCC-GARCH models in our analysis appears a suitable approach for taking into consideration any time-varying volatility in clusters.

Figure 2: Real Bist100 returns

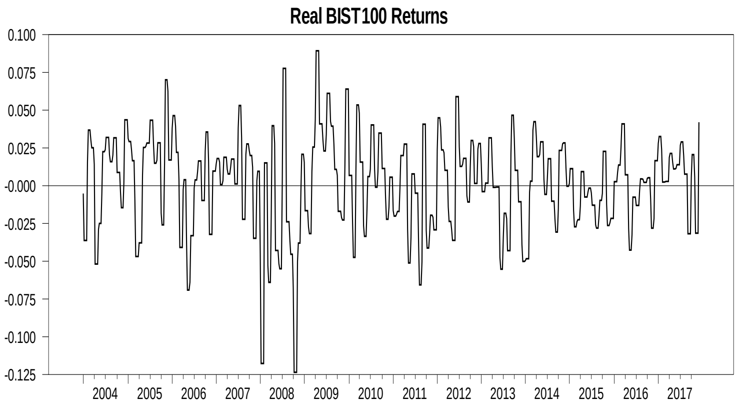
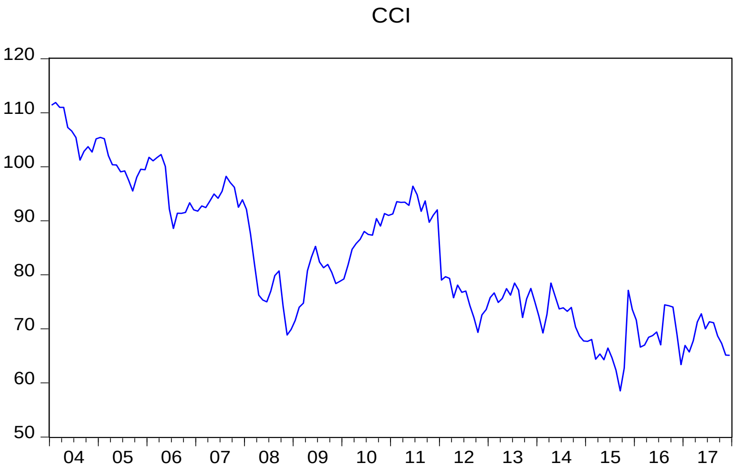


Figure 3: Consumer Confidence Index



Source: Authors' results

Figs. 2 and 3 also afford an indication of time-varying volatility for BIST100 returns then the CCI. Graphs 4 and 5 show the volatility for both CCI and BIST100 returns, and the latter is clearly more volatile than the former.

The volatility in BIST100 returns and the CCI, as shown in the above graphs, was a result of various events. The main important events are distributed over four points in time. In 2008, we noticed an acute fall that can be explained by three main events: the effects of the subprime crisis, Turkey's crisis about Islamic headscarves in university, and the trial of 86 people who were accused of planning a military coup. Two years later, another fall relates to the spread of the Arab Spring to more countries, including neighboring Syria. In addition, in October 2011, PKK rebels killed 24 Turkish troops near the Iraqi border, the deadliest attack against the military since the 1990s. Later on, the Turkish government encountered one of the biggest protests in Turkish history during the summer of 2013. Later that year in December, Erdogan was able to present the espionage case with Turkish and Iranian agents who were under the diplomatic cover of the Iranian embassy or consulates as an attempt to overthrow his government, orchestrated by his political opponents, and a number of prosecutors were excluded from the case, while police officials and officers were re-appointed and the investigation of Zarrab and the ministers was dropped. After transferring police officers from the counterterrorism unit to various positions and cities, they arrested nearly all of them on charges of plotting against the government in 2014. Finally, in 2015, Turkey shot down a Russian military jet in Syria. Russia, Turkey's second-largest trading partner, then imposed economic sanctions. In the same year, two suicide bomb attacks on an Ankara peace rally killed 100 people.

Figure 4: Conditional variance CCI

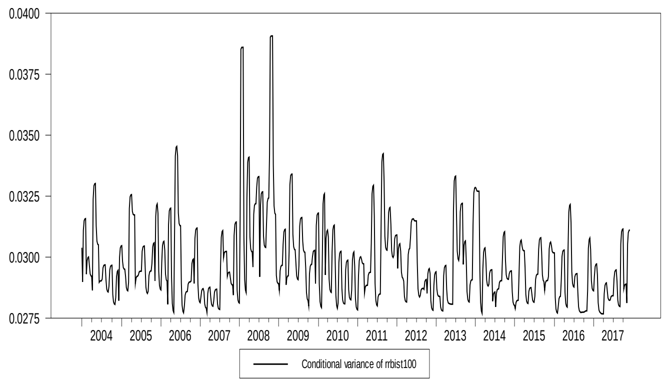
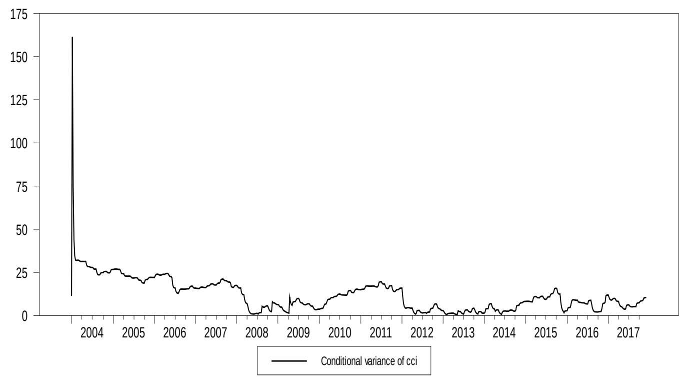


Figure 5: Conditional variance BIST100



Source: Authors' results

Table 2 gives the estimation results of our VAR-unrestricted BEKK-GARCH (1, 1) and VAR-DCC-GARCH (1, 1) models. We estimated with two models to learn which model (DCC or BEKK) is superior. When we applied the ARCH test to detect the problem of heteroscedasticity, we could not accept the null hypothesis. For the problem of autocorrelation, there is also a rejection of the null hypothesis, so there is no autocorrelation. When discussing the significant coefficients in the BIST100 mean returns equation, CCI mean return equation, and GPR index mean return equation, we find a significant negative effect from increased geopolitical risk on the CCI for both the VAR-BEKK- and VAR-DCC-GARCH models, but on the stock market, there is a negative and significant effect only in the first year. It seems that geopolitical instability like conflict between countries, violence, and other problems can affect the confidence of consumers and therefore their purchasing decisions. Real options analysis (AOR) is a financial investment decision-making tool, directly inspired by the Arrow options theory (1959). This theory takes into consideration the flexibility of geopolitical events making investment decisions as a situation of uncertainty and investors get caught up in negative sentiment, so they opt to delay investment when it may be costly. This result is in line with the work of Shahzadand et al. (2017), who employed the novel technique of nonparametric causality-in-quintiles to examine the predictability of stock returns. On the other hand, the significant negative effect of the GPR index on BIST100 stock returns can be explained theoretically through Pastor and Veronesi's (2013) reasoning about how policy uncertainty affects stock market volatility. This result is also in line with the findings of Liu and Zhang (2015) and Kang and Ratti (2013).

The influence of indirect effects and significant positive effects can be interpreted as an uncertain geopolitical state affecting the stock market (BIST100) covariance (see coefficient $\beta_{33}\beta_{31}$). We can see this on Graph 6, which presents the evolution over time of geopolitical risk together with the conditional correlation between CCI and BIST100. Indeed, as Shleifer and Summers (1990) have stated, investors are not necessarily rational, yet investor sentiment is a determinant of price. The presence of disturbances in the business climate, such as geopolitical risk, makes investors shift from being rational to being classified as arbitragers and noise traders. When we compare the persistence of volatility, the results of the variance equation show that it is lower for the stock market ($\beta 11$) than for the CCI ($\beta 22$). In addition, the impact of the GPR index on CCI variability is clearly more substantial than it is on the stock market (compare the α_{11} and α_{22} coefficients).

Table 2: VAR-BEKK-GARCH (1,1)-in-mean model estimation results.

	Variable	Model 1 VAR-DCC-GARCH (1,1)		Variable	Model 2 VAR-BEKK-GARCH (1,1)	
		BIST100- CCI -GPR			BIST100- CCI -GPR	
		Coeff	p-value		Coeff	p-value
BIST100 mean return equation	Const t	-0.001	0.000	Const t	0.01018791	0.041
	BIST100t-1	1.023	0.000***	BIST100t-1	1.058	0.000***
	BIST100t-2	-0.028	0.000***	BIST100t-2	-0.356	0.000***
	CCIt-1	0.00002	0.000***	CCIt-1	0.0001	0.004***
	CCIt-2	-0.00001	0.000***	CCIt-2	-0.0002	0.004***
	GPRt-1	-0.000002	0.0004***	GPRt-1	-0.00006	0.046**
	GPRt-2	0.000004	0.000004***	GPRt-2	0.00002	0.470
CCI mean return equation	Const.	0.050	0.000***	Const.	2.242	0.000***
	BIST100t-1	0.112	0.001***	BIST100t-1	5.629	0.001***
	BIST100t-2	0.194	0.00001***	BIST100t-2	1.109	0.544
	CCIt-1	1.021	0.000***	CCIt-1	0.998	0.000***
	CCIt-2	-0.021	0.000***	CCIt-2	-0.018	0.000004***
	GPRt-1	-0.0002	0.000001***	GPRt-1	-0.003	0.000***
	GPRt-2	-0.00003	0.601	GPRt-2	-0.002	0.043**
GPR mean return equation	Const.	0.125	0.012**	Const.	38.319	0.000***
	BIST100t-1	0.535	0.133	BIST100t-1	-30.793	0.1295
	BIST100t-2	-0.969	-0.969	BIST100t-2	-26.850	0.199
	CCIt-1	-0.024	0.000***	CCIt-1	-0.420	0.000***
	CCIt-2	0.022	0.000***	CCIt-2	0.133	0.0008***
	GPRt-1	1.022	0.000***	GPRt-1	1.077	0.000***
	GPRt-2	-0.023	0.000***	GPRt-2	-0.195	0.000***
Variances-covariance equations	C1	0.0001	0.000***	C11	0.008	0.000***
				C21	-0.054	0.382
	C2	0.379	0.000***	C22	0.198	0.161
				C31	1.011	0.183
	C3	117.938	0.000***	C32	1.395	0.644
				C33	6.602	0.000***

	Variable	Model 1 VAR-DCC-GARCH (1,1)	Variable	Model 2 VAR-BEKK-GARCH (1,1)		Variable
		BIST100- CCI -GPR		BIST100-CCI -GPR		
	α_1	18.274	0.000***	α11	0.685	0.000***
				α12	-11.548	0.000***
				α13	96.463	0.003***
	α_2	18.846	0.000***	α21	-0.0008	0.246
				α22	0.637	0.000***
				α23	0.654	0.217
	α_3	18.556	0.000***	α31	0.0001	0.007***
				α32	0.005	0.125
				α33	0.566	0.000***
	β_1	0.251	0.000***	β11	0.608	0.000***
				β12	19.633	0.000***
				β13	-12.278	0.672
	β_2	0.304	0.000***	β21	-0.0012	0.014**
				β22	0.787	0.000***
				β23	0.917	0.001***
	β_3	0.244	0.000***	β31	-0.0001	0.017**
				β32	-0.015	0.000***
				β33	0.698	0.000***
	DCC(A)	0.945	0.000***			
	DCC(B)	0.054	0.000***			
Diagnostics	**GEDparameter**					
	Usableobservations	726			726	
Loglikelihood		-898.074			-1850.862	
	Res.BIST100 equ	**Res.CCI equ**	**Res.GPReqn**	**Res.BIST100 equ**	**Res.CCI equ**	**Res.GPReqn**
Ljung-boxQ(12)*p*-value	0.45	0.42	0.06	0.43	0.43	0.07
McLeod-Li(12)*p*-value	0.97	0.98	0.95	0.96	0.98	0.06
ARCH(4)test*p*-value	0.97	0.98	0.95	0.96	0.98	0.95

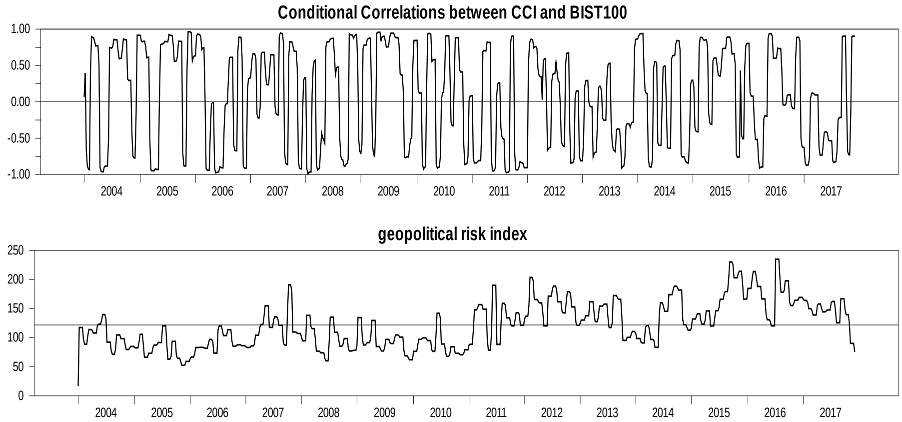
Source: Authors' results. Note: (***), (**) and (*) denote significance at 1% and 5% and 10%, respectively.

The extent of the volatility transmission between the CCI, BIST100 returns, and the GPR index is very interesting. Our findings show that past geopolitical risk plays a crucial role in explaining the temporal dynamics of conditional volatility for the BIST100 in Turkey, so this should also be accounted for when making volatility forecasts for future stock returns. This result is justified by Lensink et al. (2000), who states that an increase in political risk leads to an increase in capital flight. This is also justified by Diamonte et al. (1996), who found that portfolios that experience lower political risk also generated larger returns than portfolios with a greater degree of political risk. They also posited that emerging markets are more vulnerable to political instability than developed markets. Moreover, the conditional volatility of geopolitical risk causes significant changes in BIST100 returns ($\alpha 1$). A shock to the Turkish stock market, regardless of direction, therefore implies an increase in the volatility of the GPR index. On the other hand, the past geopolitical risk, as represented by β_2, has a significant effect on the CCI. This can be explained by the fundamental psychological motivations of investors, which can in themselves affect the stock markets. Pompian (2012) calls them emotional biases that can lead people to make suboptimal decisions. We should therefore expect to see a close interaction between human behavior and financial parameters. As a result, governments, central banks, and other regulators and supervisors pay particular attention to the management of expectations and perceptions. Investor sentiment (CCI) is one of the most important indicators that reflects expectations and perceptions.

We notice that the parameters β and α associated with the DCC model are statistically significant. On the other hand, we assert that the existence of a behavior of current variances is more influenced by the magnitude of past variances than by past performance innovations. Another remark that we can put forward is that the conditional correlation between the pairs of indices is not constant this is because of the positivity of the sum of the parameters of the model DCC ($\alpha+\beta$).

In Figure 6, the dynamic conditional correlation curve between the CCI index and the BIST100 returns is above compared with the Turkish GPR index curve. In addition, conditional correlation between the CCI index and BIST100 returns exists as a dynamic conditional correlation depending on the time change. However, as shown in figure 6, the coefficient is sometimes large and sometimes small, and the estimated conditional correlations have increased in recent years (2011, 2015 and 2016), implying greater linkage between BIST100 returns and the CCI when the GPR index is high. This may provide a clue for policy developers. We can clearly see that these two indices vary in a different way over time. Then a "coupling" effect is present because of the value of the coefficient which approaches 0.22. This indicates that the two indices are correlated.

Figure 6: Geopolitical risk index versus conditional correlations between CCI and BIST 100 returns



Source**:** Authors' results.

5. Conclusion

In the existing literature, no study has attempted to discuss the impact of geopolitical risk and investor sentiment on stock returns. This paper also complements several studies that have measured the economic and/or financial consequences of war, tension between states, terrorist attacks, and other forms of large-scale violence.

This study used the recently proposed monthly geopolitical risk (GPR) index (Caldara and Iacoviello, 2018) to observe the effects of global tension, friction, and conflict on Turkish stock returns and consumer confidence. Three indices were therefore used in this empirical investigation for a period from January 2004 to December 2017, namely the GPR index, the CCI, and the BIST100 stock index. Our study employed VAR-BEKK-GARCH and VAR-DCC-GARCH models to allow the modeling of mean returns and the variance with the covariance.

Our findings show that the CCI seems to be more affected by the GPR index in terms of mean return and variability than the stock market index. This agrees with the work of Mustafa and Hamid (2013). Moreover, the conditional covariance between the CCI and BIST100 stock index was significantly affected in three periods: the 2008 subprime crisis, the Arab spring in 2011, and the coup attempt in Turkey on July 15, 2016. This provides evidence of international convergence and integration and may provide a clue to policy developers for public management. As many studies have revealed, globalized markets respond to major political events (Çam, 2014; Kaya et al., 2015; Samet Günay, 2016).

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