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Papadamou, Stephanos and Fassas, Athanasios and Kenourgios, Dimitris and Dimitriou, Dimitrios

University of Thessaly, University of Athens

2 May 2020

Direct and Indirect Effects of COVID-19 Pandemic on Implied Stock Market Volatility: Evidence from Panel Data Analysis

Stephanos Papadamou[*]

Department of Economics, Laboratory of Economic Policy and Strategic Planning, University of Thessaly, Greece

Athanasios P. Fassas

Department of Accounting and Finance, University of Thessaly, Greece

Dimitris Kenourgios

Department of Economics, UoA Center for Financial Studies, National and Kapodistrian University of Athens, Greece

Dimitris Dimitriou

Department of Economics, UoA Center for Financial Studies, National and Kapodistrian University of Athens, Greece

Abstract

We investigate the effects of a google trend synthetic index concerning corona virus, as a composite indicator of searching term and theme, on the implied volatility of thirteen major stock markets, covering Europe, Asia, USA and Australia regions by using panel data analysis along with several model specifications and robustness tests. Increased search queries for COVID-19 not only have a direct effect on implied volatility, but also have an indirect effect via stock returns highlighting a risk-aversion channel operating over pandemic conditions. We show that these direct and indirect effects are stronger in Europe relative to the rest of the world. Moreover, in a PVAR framework, a positive shock on stock returns may calm down google searching about COVID-19 in Europe. Our findings suggest that google based anxiety about COVID-19 contagion effects leads to elevated risk-aversion in stock markets. Understanding the links between investors' decision over a pandemic crisis and asset prices variability is critical for understanding the policy measures needed in markets and economies.

JEL codes: C33; D83; G12; G14

Keywords: COVID-19 pandemic; google trends; implied volatility; stock returns; panel data

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[*] *Correspondence author.* Address: 78, 28th October Str., Volos 38333, Greece. E-mail: stpapada@uth.gr

1. Introduction

The coronavirus disease 2019 (COVID-19) is the first global deadly pandemic after more than a century (the last one was the 1918 flu pandemic, also known as the Spanish flu). The first known outbreak of COVID-19 was around the end of 2019 in China and in less than three months, it spread across the globe, causing a huge number of infections and deaths over more than 200 countries. The future economic impact of this pandemic is still highly uncertain and thus, in this setting, it would be interesting to investigate the incorporation of information related to coronavirus into equity indices performance, as measured by return and volatility.

This paper investigates the link between the dynamics of implied volatility indices in thirteen countries across the globe and investor attention as measured by Google search probability in the era of Covid-19. Scholars are coming to recognize the predictive value of data collected across various digital platforms, with search behavior data being an extremely abundant repository of predictive data. Google search query data are increasingly being used in the literature across several disciplines for measuring variables and phenomena ranging from the spread of flu (Ginsberg et al., 2009; Polgreen et al., 2008) and election outcomes (Metaxas and Mustafaraj, 2012), through tourist numbers (Choi & Varian, 2012) to consumer behavior (Carrière-Swallow and Labbé, 2013) and economic statistics and key economic figures (Choi and Varian, 2012). In finance, search queries provided by Google have proved to be a useful source of information for studying domestic bias in international equity holdings (Mondria et al., 2010), earnings announcements (Drake et al., 2012), trading strategies (Preis et al., 2013), traded volume (Preis et al., 2010) and portfolio diversification (Kristoufek, 2013).

Based on the assumption that information is instantaneously incorporated into prices when it arrives, Da et al. (2011) are the first to propose a new and direct measure of investor attention using search frequency in Google. Since then, an emerging literature documented the impact of investors' attention on asset market microstructure and asset prices and volatility (Joseph et al., 2011; Vlastakis and Markellos, 2012; Smith, 2012; Vozlyublennaia, 2014; Ding and Hou, 2015; Dimpfl and Jank, 2016; Goddard et al., 2015; Chronopoulos et al., 2018). However, there is no relevant study that directly studies investors' attention in a period of crisis. Our paper is motivated by the papers of Andrei and Hasler (2015), who develop a

theoretical model that shows how investors' attention affects the dynamics of asset returns, and Da et al. (2015), who find that internet search volume for relevant terms such as "recession" and "unemployment" is contemporaneously related to the S&P 500 VIX. Against this background, the current study extends this literature, by measuring investor attention to the coronavirus pandemic, following a similar approach to Da et al. (2011), and analyzing the relation between the Internet search activity and implied volatility in a period of extraordinary stress and uncertainty. In particular, we form four main research questions to be answered: (1) Does investors' attention as proxied by Google's search volume index add information to stock market implied volatility? (2) Does investors' attention as proxied by Google's search volume index significantly affects equity indices returns? (3) Do the dynamics of the relationship between stock index returns and changes in volatility change in times of crisis? (4) Do investors demand more information during periods of pandemic shocks? In this set up, we construct a synthetic index based on "corona virus" term and "corona virus" theme as a direct proxy for investors' attention, and use a sample of equity and implied volatility indices of thirteen countries around the world.

The current study also contributes to two additional strands of literature. First, we add to the several studies (see Kollias et al. 2013 and Liu et al., 2019 for a relevant discussion) that examine how markets and market agents react to exogenous events, such as natural disasters, social unrest, political upheavals and violent events; search queries data extends existing attempts, as it measures the public's attention to unexpected catastrophic events and gives timely feedback on investment dynamics (Liu et al., 2019). Second, we also contribute to the contemporaneous, but exponentially growing, literature on the effects of COVID-19 on economic activity (Baldwin and Weder di Mauro, 2020; Duan et al., 2020; Atkeson, 2020; Eichenbaum et al., 2020), on economic sentiment (Baker et al., 2020a,b) and on financial markets (Alfaro et al. 2020; Corbet et al.,, 2020(a); Corbet et al. 2020(b); Ramelli and Wagner, 2020; Zhang et al., 2020; Gormsen and Koijen, 2020).

Our main findings are summarized as follows: first, we identify short-run causality from Google search queries data to implied volatility dynamics. Second, there is a negative short-run effect of Google searches to equity indices returns. Third, there is evidence that the persistence (leverage effect) in the VIX becomes stronger as Google search queries intensify. Fourth, Google carries different short-run predictive

information in Europe relative to the rest of the world. Finally, we show that a positive shock on stock returns may calm down google searching about COVID-19 in Europe. The rest of the paper is organized as follows. Section 2 presents the literature review and the hypotheses to be tested. Section 3 presents the data sample and a preliminary analysis, while the description of the methodology is presented in Section 4. The empirical results and a robustness analysis are presented and discussed in Section 5. Section 6 reports the summary and concluding remarks.

2. Background and hypotheses

2.1 Literature Review

Our paper attempts to contribute to the recent path of literature that studies the effects of investors' attention, as proxied by Google search volume, on financial assets. A literature studying the impact of investor attention on the dynamics of asset prices (see, e.g., Baker and Wurgler, 2007 and Bekaert et al., 2019 for a review) has emerged during the last two decades. One important channel through which investors express their demand for information is through internet searches (Drake et al., 2012). The appeal of search-based sentiment measures is more transparent when compared with alternatives (see Da et al., 2015 for a discussion).

Da et al. (2011) was the first study to treat Google Search as a direct measure of investor attention; their empirical findings show that an increase in search volume for Russell 3000 stocks predicts higher stock prices in the next two weeks. Subsequently, several papers studying the connection between investor attention, as measured by search queries, and market returns and volatility have emerged over the recent years. Indicatively, studies documenting this link includes Joseph et al. (2011), Drake et al. (2012), Vlastakis and Markellos (2012), Irresberger et al. (2015), Bijl et al. (2016), Dimpfl and Kleiman (2019), Chen and Lo (2019) and Kim et al. (2019) for individual stocks, Dzielinski (2012), Vozlyublennaia (2014), Hamid and Heiden (2015), Da et al. (2015), Chronopoulos et al. (2018), Dimpfl and Jank (2016) and Graham et al. (2019) for stock indices, Goddard et al. (2015) and Smith (2012) for exchange rates, Vozlyublennaia (2014) and Dergiades et al. (2015) for bonds, Vozlyublennaia (2014) and Afkhami et al. (2017) for commodities, Da et al. (2015) for ETFs, Yung and Nafar (2017) for REITs and Philippas et al. (2019) for Bitcoin.

Extensive research has documented the effect of investors' attention on asset prices and volatility, but only a very limited number of studies have investigated the link of investors' attention to implied volatility, one of the most popular market-based measures of investor sentiment (Whaley, 2000). In particular, Vlastakis and Markellos (2012), Da et al. (2015) and Ruan and Zhang (2016) show that investors' attention is significantly positively related to implied volatility, while Nikkinen and Peltomäki (2020) show that the effects of information demand on realized stock returns and the VIX index are instantaneous.

2.2 Testable Hypotheses

We test four hypotheses to analyze the relationships between investors' attention, as proxied by Google search queries, and market aggregate risk-return dynamics. Empirical research in finance has long been investigating the link between volatility and the rate at which information flows into financial markets (see Kalev et al., 2004 and Da et al., 2011 for a review of the relevant literature), as one of the most intuitive explanations for commonly-observed volatility patterns is that volatility is proportional to the rate of information arrival (Smith, 2012). As a result, the first hypothesis is as follows:

H1. Investors' attention as proxied by Google's search volume index adds information to a market-based measure of volatility.

Our second hypothesis stems from the attention-induced price pressure hypothesis of Barber and Odean (2008) and claims the following:

H2. Investors' attention as proxied by Google's search volume index has a significant effect on equity indices returns.

The third hypothesis relates to one of the most noticeable stylised facts in finance; the negative correlation of stock index returns with changes in volatility (French et al., 1987). Our scope is to investigate whether, in times of the pandemic crisis, the dynamics of this relationship are altered. Thus, the third testable hypothesis is formed as follows:

H3. The volatility feedback hypothesis becomes stronger (weaker) in periods of anxiety.

Finally, relatively scant empirical evidence (Vozlyublennaia, 2014; Vlastakis and Markellos, 2012; Goddard et al., 2015; Andrei and Hasler, 2015) shows that investors demand more information as a shock to index returns occurs and as the level of risk aversion increases. Given these findings, the forth hypothesis is as follows:

H4. Stock market anxiety and shocks results in an increase of investors' attention.

3. Data and preliminary analysis

The development of COVID-19 in late 2019 on China and the contagion on other Asian, European countries, USA and Australia over the beginning of 2020 lead us to focus on a sample period from 02 January 2020 to 09 April 2020. Google trends metrics provide useful information concerning the attention of the crowd on epidemy of COVID-2019 over this period. The metrics achieve the highest 100 hundred level on the day of this period where attention is highest and the rest days are presented reference to that. Following this methodology, we decided to construct a synthetic index based on "corona virus" term and "corona virus" theme. The former is a specific search term while the latter refers to a general term concerning heath consequences of a severe heath decease. By constructing this synthetic indicator, we may highlight any time variation from the early beginning of 2020 and over the first four months. The end of sample period coexists with the closing of the stock markets for Easter holidays in USA and most European countries. Our thirteen sample countries selection is based on the availability of an implied volatility index and the existence of coronavirus victims. Therefore, we use data on general stock market indices and implied volatility indices for Germany (DEU), France (FR), Italy (IT), Netherland (NL), United Kingdom (UK), Switzerland (CH), Russia (RUS), China (CHN), India (IND), Japan (JPN), Korea (KOR), United States of America (USA) and Australia (AUS).

<Insert Figures 1a,b about here>

Figures 1a,b, 2, 3 include the graphical depiction of the three variables of interest, Google Trend Metric, Implied Volatility, and Stock Prices, for each country on a vertical manner. By looking on European countries in Figures 1a,b, the beginning of search concerning COVID-19 can be placed in the middle of January (specifically the indicator takes off on day 20/01/2020). However, this is also true for all countries

in the sample (see Figures 2 & 3). By looking these figures, the first wave of increase in google trend indicator concerning COVID-19 coexist with a small increase on implied volatility and a short decline to stock prices (this effect seems to be clearer in China and Korea relevant to the rest countries). Over the second wave of increase in google trend indicator beginning on 19/2/2020, the drop on stock prices and the increase of implied volatility are common and unified across all countries and regions.

<Insert Figure 2,3 about here>

Given that Figures 1a,b, 2, 3 leave no doubts of non-stationary series, we proceed on first logarithmic changes[1] in order to investigate stationarity via panel unit root tests. Therefore, the first step of our empirical investigation involves a number of panel unit root tests applied on these changes (VIX_changes, GTR_changes, Stock_changes). The results (included in Table 1) indicate strong evidence against non-stationarity for the changes of all series under review. Here on, our focus will be on changes more than level data.

<Insert Table 1 about here>

Assumed the well-known negative relationship between stock market returns and stock market implied volatility in finance (Whaley, 2000), we come to assess firstly any direct impact of Google Trend metric concerning COVID-19 on stock market implied volatility, and secondly any indirect effect working via this well-known relationship. More specifically, we expect that uncertainty concerning a spread of a pandemic with dangerous health results adds on future stock market volatility measured by the implied volatility measure, but also may strengthen in absolute terms the relationship between stock market returns and implied volatility changes. A significant drop on stock market may increase implied volatility more in a contagion environment of a pandemic.

In order to have a preliminary picture of the relationship pattern between VIX and stock market indices, we apply the dynamic conditional correlation approach (DCC) of Engle (2002). DCC is a parsimonious estimation technique of a dynamic correlation between two series and provides useful information on their correlation

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[1] For the google trends indicator, we construct and indicator equals to log(e + Google Trend Metric value) similarly to Eckstein & Tsiddon (2004) followed on terrorism attacks. Then, we take first logarithmic differences on this indicator as we do with implied stock market volatility indices and stock prices indices.

fluctuations over time. The level of DCC correlations between VIX and stock market returns over the period 02/01/2020 through 09/04/2020 is shown in Figure 4.

<Insert Figure 4 about here>

At all points, the degree of correlation between the series is found to be low, with magnitude less than -0.2 in most cases. However, it is worth highlighting the change of correlation near and after the milestone dates of January 20, 2020 and February 19, 2020. The level of correlation fluctuates considerable during these periods, supporting changes in investors' appetite for risk. This change is asymmetric and depends heavily to the market under examination. However, while DCC provides information on the correlation characteristics of our series over time, it sheds no light on the causal effects among series. This supports the use of panel data techniques for examining the series behavior in more depth, by including more explanatory variables.

4. Methodology

The short-time period covered of the COVID-19 leads us to study thirteen countries with daily data for almost three and half months in a panel data framework. Panel data estimation allows us to control for individual heterogeneity and reduces estimation bias (Wooldridge, 2002).

Firstly, following previous literature indicating the strong relationship between volatility and return (Fleming et al., 1995; Bekaert and Wu, 2000; Bollerslev et al., 2006; Hibbert et al., 2008; Fernandes et al., 2014), we formulate a model that incorporates any possible GTR effects on volatility changes as shown below:

$$VIX_{changes_{i,t}} = a_0 + a_1 GTR_{changes_{i,t}} + a_2 GTR_{changes_{i,t-1}}$$

$$+ a_3 Stock_{changes_{i,t}} + a_4 \left(Stock_{changes_{i,t}} \times GTR_{changes_{i,t}} \right)$$

$$+ a_5 \left(Stock_{changes_{i,t}} \times GTR_{changes_{i,t-1}} \right) + \mu_i + \varphi_t + e_{i,t} \tag{1}$$

where, $VIX_{changes_{i,t}}$ measures the rate of change on stock market implied volatility (i corresponds to each country of the sample and t on each day of the sample) and $Stock_{changes_{i,t}}$ refers to stock market price daily changes for each cross section i,

while the rate of change on google trend measurement about COVID-19 is measured for each country i over day t by the $GTR_{changes_{i,t}}$ and can also be treated as an independent variable. As can be seen in our model, given that we don't know whether Google trend variable affects contemporaneous or in a time lag the changes on VIX, we estimate a wider model allowing for time dynamic direct and indirect effects.

Under this specification, the a_1, a_2 coefficients capture any direct effects of the uncertainty concerning COVID-19 epidemic on risk taking at stock markets, as proxied by implied volatility. If anxiety about the future possible negative social and/or economic effects of the pandemic does directly discourage risk-taking, we expect the a_1 and/or a_2 coefficient to be positive and statistically significant. However, in our model we can also quantify any indirect effect working via the well-known negative relationship (we expect $a_3 \leq 0$, and statistically significant) between stock returns and implied volatility changes. More specifically, we expect that a cross-term of stock returns with the Google Trend metric may increase in absolute terms this negative relationship (we expect $a_4 \leq 0$ or $a_5 \leq 0$, and statistically significant).

The parameter a_0 represents the overall constant in the model, while the μ_i and φ_t represent respectively the cross section and time specific effects (random or fixed). The $e_{i,t}$ are the error terms for i=1, 2, …, 13 cross-sectional units, observed for t=1, 2, …,T daily periods. This model can help us investigating any significant contemporaneous and/or dynamic relationship between the variables of interest. Furthermore, since the futures market data essentially captures all relevant information regarding the stock market under review, we can quantity the response of investor sentiment to an epidemic anxiety shocks more effectively.

Secondly, in order to investigate any causality between implied stock market volatility changes, stock market returns and Google Trends changes, we proceed to the estimation of a panel VAR model including $VIX_{changes}$, $Stock_{changes}$ and $GTR_{changes}$ as endogenous variables, using the GMM estimator of Abrigo and Love (2016). Impulse response analysis and variance decomposition may highlight any significant causal effects and any time delayed response of variables of interest. Therefore, our general first order PVAR model is defined as follows:

$$Z_{i,t} = \Gamma_0 + \Gamma_1 Z_{it-1} + f_i + e_{i,t} \qquad (2)$$

in which, $Z_{i,t}$ is a three-variable vector $\{VIX_{changes},\ Stock_{changes}, GTR_{changes}\}$. This panel VAR models allows for "individual heterogeneity" in the levels of the variables by introducing fixed effects, denoted by f_i in Equation (2).

5. Empirical Results

Table 2 presents the estimation results for the pooled, fixed and random effects models regarding Equation (1). In the upper part of column (1) the independent variables of the models are presented, while in the lower part some diagnostics and specification tests are also provided. In column (2) the expected signs of the coefficients of interest are given. We follow a top-down econometric approach, beginning with a wide model including all variables of the model presented in equation (1), and finally keeping only the statistically significant ones (the results of this reduced model are presented in Table 2).

<Insert Table 2 about here>

In terms of estimation methods, we begin with the pooled estimation and by conducting a fixed versus pooled estimation F-test, we proceed with the one that is suggested by the test. We conduct a cross section and a period F-test in order to select the most suitable model. Moreover, the Hausman test helps us in order to select between Fixed and Random Effects models, by giving a small lead to the latter. However, for reason of consistency and robustness we present the results of all types of estimation methods. We have to mention at this point that the results of the Frees test for cross-sectional correlation in fixed effect and modified Wald test for group-wise heteroskedasticity leads us to use panel corrected standard errors in all of our estimations (PCSE).[2]

By looking at the columns of Pooled, Fixed and Random Effects models, we can conclude that: (a) stock returns increases coexist with reductions on implied volatility changes; (b) the direct effect of Google trend on COVID-19 pandemic is positive, contemporaneous only, and statistically significant at the 1% and 5% level of significance; and (c) the indirect effect is dynamic and significant also. More specifically, based on our findings, an increase in Google Trend about COVID-19

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[2] According to Beck and Katz (1995), the existence of cross-panel correlations, if not corrected, will result to inefficient estimates even if heteroskedasticity is controlled for.

pandemic over the previous day can strengthen the negative relationship of stock returns on the returns of implied volatility of the stock index. However, this is not happening contemporaneously. Our three main findings are robust across the estimation methods applied on the reduced model that keeps only the statistically significant variables presented in Table 2. The constant term in all cases is positive and statistically significant, reflecting an average daily VIX change. The R-squared across all estimations varies between 34.5% and 56.3%, with the highest value on the model without cross section (or country) effects, but with time effects.

In the next step, given the values of the Durbin-Watson tests and allowing the residuals to follow an autoregressive one process, we proceed to the estimation of the reduced model with the Pooled OLS[3] / Fixed Effects with PCSE and an AR(1) term common across all cross sections. The results of these estimations are presented in the right last two columns of table 2. In terms of magnitude of the three coefficients of interest, all are higher in absolute terms in both two cases of estimation, without reducing statistical significance. The negative statistically significant value of the coefficient of the autoregressive term implies a mean reversion process on VIX changes across all stock markets in those thirteen countries studied.

We continue our empirical analysis by investigating whether there is any feedback effect across the three variables of interest in a PVAR framework. The impulse response analysis can highlight the magnitude of the effect during the time and, most important, the direction of the effect across the three variables. Following recent behavioral finance developments (see Baker and Wurgler, 2007 for a discussion), market reactions are reflected on price changes or VIX changes given that discount future events may calm down crowd in searching over internet media or the completely opposite by adding more anxiety.

The GMM estimation in a PVAR framework allow us to treat any bi-directional relationship between return and volatility in the stock market across all 13 countries, but also any bi-directional or uni-directional relationship between Google Trend metrics about COVID-19 epidemic and the other two stock market variables.

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[3] In the case of heteroskedastic and contemporaneously correlated across panels disturbances, the combination of OLS with panel-corrected standard errors (PCSEs) leads to an accurate estimation compared to the feasible generalized least squares (GLS) method (Beck and Katz, 1995).

Impulse response analysis in Figure 5 highlights clearly the direction of these interdependencies.

<Insert Figure 5 about here>

As expected, a positive shock on stock market returns reduces significantly implied volatility in the relevant market by reaching its bottom immediately and dies off after almost two days. However, a bi-directional relationship between these two variables seems to be present in some degree, since the response of stock returns to a positive implied volatility shock is negative, reaching its bottom after one day and disappearing after two days.

By focusing on the last row of diagrams in Figure 5, we observe that a positive shock on Google search for COVID-19 pandemic has an immediate statistically significant positive effect on stock market implied volatility and a clear negative effect on stock returns. In both cases, this effect diminishes after two days. By looking at diagrams in the diagonal, VIX changes and GTR changes present a quite similar pattern as long as their autoregressive part are considered in contrast to stock changes.

By looking at the response of Google trend changes about COVID-19 pandemic to a positive shock on stock changes and vix changes respectively, we can highlight the following two points. On the one hand, a positive shock of stock returns reduces significantly the rate of searching about COVID-19 pandemic. The leading indicator role of stock market about future economic activity and possible consequences of a pandemic on the economy leads to calm down searching implying or discounting low consequences from this pandemic. On the other hand, a positive shock on implied stock market volatility seems to increase searching for COVID-19 pandemic and its consequences. However, as can be seen by the confidence bands, there is no statistically significant relationship in this case.

Table 3 report the results from the variance decomposition analysis for our basic PVAR model. The first column of Table 3 presents the response variable and its forecast horizon. As can be seen, Google trend search variability for COVID-19 is mainly explained by itself. However, the total effect accumulated over 3 days reported for stock changes variability and Vix changes variability by Google Trend changes concerning COVID-19 epidemic indicate the followings: (a) The Google Trend metric changes variability explains 2% of stock prices changes and 3.3% of Vix changes; (b)

The percentage of stock prices variability explained by the Google trend COVID-19 metric (2.08% after 3 periods) is higher than those explained by the Vix changes (0.71%), highlighting the importance of variability induced by an epidemic contagion versus implied stock market volatility on stock returns. Worth mentioning at this point the important percentage of vix changes variability explained by the stock returns after a three-period time (27.66%). Together social attention on COVID-19 epidemic and stock returns explain 30% of VIX changes variability.

<Insert Table 3 about here>

5.1 Robustness check

By experimenting with different groups of stock markets, we investigate the robustness of our central findings. In particular, we re-estimate Equation (1) in its reduced form as appeared in Table 2 by decomposing the effect of each coefficient (concerning direct and indirect effects of Google Trend metric about COVID-19 on Vix changes) on two groups: The European versus non-European markets and the Asian versus non-Asian markets.[4]

A particular dummy (D_j) is constructed, taking the value of one if market k belongs to *j* group (j takes value European or Asian markets) and zero otherwise. Similarly, the dummy ($1 - D_j$) is constructed, taking the value of one if market k does not belong to *j* group (i.e. non-European or non-Asian markets) and zero otherwise. Therefore, model 2 (the reduced model) is re-estimated as follows:

$$VIX_{changes_{i,t}} = b_0 + b_1^a \left[(D_j) \times GTR_{changes_{i,t}} \right] + b_1^b \left[(1 - D_j) \times GTR_{changes_{i,t}} \right]$$

$$+ b_2 Stock_{changes_{i,t}} + b_3^a \left[(D_j) \times \left(Stock_{changes_{i,t}} \times GTR_{changes_{i,t-1}} \right) \right]$$

$$+ b_3^b \left[(1 - D_j) \times \left(Stock_{changes_{i,t}} \times GTR_{changes_{i,t-1}} \right) \right] + \mu_i + \varphi_t + e_{i,t} \qquad (3)$$

Our attention is given on the comparison between b_1^a and b_1^b referring to "direct effects of GTR changes on Vix" and b_2^a and b_2^b referring to "indirect effects of GTR changes on Vix", between *j* group versus rest markets each time.

<Insert Table 4 about here>

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[4] Given that the cases of Australia and USA construct a group with smaller observations, we decided to focus on the European/non-European, Asian/non-Asian markets. However, comparisons of the findings among the two groups have direct implications for the other two countries.

Table 4 presents the results in line to Table 2. The only difference is that for each estimation method we present two different columns; one for the estimation of European markets versus non-European markets and another for the estimation of Asian versus non-Asian markets. Therefore, index j takes values EUR for European markets or Asia for Asian markets each time. Let's, firstly, focus on European versus non-European markets results. The direct effect of GTR changes on VIX changes is higher in magnitude for European markets versus non-European markets ($b_1^a > b_1^b$). In Asian markets, the direct effect is smaller in magnitude compared to the rest markets. Additionally, when comparing the direct effect on Asian markets versus the direct effect on non-European markets, it can be implied that USA and Australia markets contributes positively relative to Asian markets. These main findings remain the same in the case that an AR(1) term is estimated, but the magnitude of the direct effect is in general increased.

Stock return is statistically significant and negatively related to VIX changes in all cases, but the magnitude of the coefficient is higher in absolute terms in Asian markets and then follows European markets. When looking on the indirect effect of Google trend searching for COVID-19 on this stock return VIX relationship, we can argue that this COIVD-19 searching when increasing strengthen this relationship in absolute terms. More specifically, this indirect effect of GTR changes on VIX via stock return channel is present and statistically significant in European and Asian markets only. Again, when looking at the magnitude of the coefficients, the European case presents the higher values.

Furthermore, in order to examine the results across different groups of stock markets using the PVAR model, we follow the same methodology of decomposing the effect of google trend searching on COVID-19 pandemic in European versus non-European markets and in Asian versus non-Asian markets. Impulse response analysis (see Figures 6 & 7) and variance decomposition (see Tables 5 & 6) confirm our previous findings that the effects are stronger for European markets versus the rest markets. Stock market returns respond negatively to an increase in searching about COVID-19 with higher statistical significance in case of European versus the rest markets. Worth also mentioning, the negative response of google trend searching for COVID-19 due to a positive stock market return shock is mainly attributed to

European markets. This implies a bi-directional relationship between stock market investing and searching about consequences of a pandemic.

<Insert Figure 6 & 7 about here>

Tables 5 and 6 report the results from the variance decomposition analysis for our two versions of the PVAR model. One for a PVAR that compares European versus non-European markets effects and the other one that compares Asian versus non-Asian markets effects. The results on these tables also confirm the relative importance of google trend searching for a pandemic both on European stock market returns and implied volatilities relative to the rest markets. For example, by looking on 3 days forecast horizon, the google trend metric about COVID-19 pandemic explains 2.49% of VIX variability in European markets relative to 1.05% to non-European markets. By comparing the value of 2.49% in Table 5 with the value of 2.67% in Table 6 referring to google trend metric explanation of the VIX in non-Asian countries, we observe the value added due to the US and Australian contribution.

<Insert Tables 5 & 6 about here>

Finally, in order to investigate further the robustness of our main findings concerning the indirect effect of the investors' attention about COVID-19 on stock returns and implied volatility changes, we proceed to the estimation of the dynamic correlations in each country from a GARCH(1,1)-DCC model. Then, we estimate any positive relationship between absolute values of these correlations with our metric about COVID-19 attention. The estimates presented in Table 7 show that an increase in COVID-19 increase in absolute terms the correlation between stock returns and implied volatility changes for all groups of countries, confirming our previous findings. The fixed effect model is preferable versus the pooled model. Moreover, the Hausman test support the fixed effect versus the Random effects model.

<Insert Table 7 about here>

6. Conclusion

The debate regarding the effects of investors' attention (Vlastakis and Markellos, 2012; Da et al., 2015) on implied stock market volatility dynamics has led

to a growing recent body of literature, but the respective empirical results of a pandemic contagion across different markets with different cultures are inconclusive and not until now explored. Direct effects of increased uncertainty due to COVID-19 expansion may contribute to higher stock market volatility, but also indirect effects via significant stock market drops may also be raised. While the relationship of stock returns and implied stock market volatility is widely acknowledged (French et al., 1987), less is known about how this relationship may be affected by a pandemic that spreads all over the world with significant economic consequences due to human infections and measures of quarantine, social distancing and economic disruption.

Our empirical findings show that there is a causal positive direct relationship between Google trend metrics for COVID-19 and stock market implied volatility. The automated trading by the increased use of technology in all over the world can make investors searching for trends in google metrics and contemporaneously make active trading on markets via electronic platforms. By studying thirteen stock markets expanding from Europe to Asia, Australia and USA, we found that this relationship is more clearly presented in European markets relative to Asian markets. Our findings also indicate that increase anxiety produced by the increased searching for consequences concerning COVID-19 pandemic and its short- or long-lasting effects on economies may strengthen the negative relationship between stock market returns and their implied volatility, supporting the volatility feedback hypothesis.

Our evidence supports the existence of a risk-aversion channel of pandemic spread in the stock market, as well as the attention-induced price pressure hypothesis. Therefore, our results compliment previous studies which show that implied volatilities in the stock markets are affected by investor attention in a "google" or "internet" based economy (Da et al., 2015). These findings highlight an investor sentiment channel that is growing via behavioral biases during pandemic crisis periods and provide useful insights to investors and policy makers. Understanding the links between investors' decision over a pandemic crisis and asset prices variability is critical for designing and implementing the policy measures needed in markets and economies. Finally, further research might help shedding light on the risk-taking monetary policy transmission channel (Delis et al., 2017; Fassas & Papadamou, 2018) and how may be affected by the expansion of a pandemic that affects investors' risk tolerance and perception measured by google trend metrics.

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Table 1. Summary of panel unit root tests

	VIX_changes				Stock_changes				GTR_changes			
Method	Statistic	Prob.**	Cross-sections	Obs	Statistic	Prob.**	Cross-sections	Obs	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)												
Levin, Lin & Chu t*	-23.431	0	13	767	-26.159	0	13	767	-19.979	0	13	767
Null: Unit root (assumes individual unit root process)												
Im, Pesaran and Shin W-sta	-23.593	0	13	767	-23.625	0	13	767	-21.332	0	13	767
ADF - Fisher Chi-square	426.631	0	13	767	424.321	0	13	767	344.034	0	13	767
PP - Fisher Chi-square	460.068	0	13	767	525.935	0	13	767	424.341	0	13	767

Notes: This table includes the panel unit root tests results for VIX changes, stock market changes and google trends indicator changes.

H_0: unit root is present. P-values are in parentheses. ***,**** and ***indicate statistical significance at the 10%, 5%, and 1% level respectively.

Table 2. Panel data estimation results for changes on stock market VIX

Dependent Variable		Vix_changes							
Independent Variables	Exp. Sign	Pooled with PCSE		Fixed Effects with PCSE		Random Effects with PCSE		Pooled OLS with PCSE and AR(1)	Fixed Effects with PCSE and AR(1)
Model		(1)	(2)	(1)	(2)	(1)	(2)	(2)	(2)
C	+/-	0.0067	0.0083	0.0108	0.0112	0.0096	0.0103	0.0078	0.0077
		(0.04)**	(0.01)**	(0.00)***	(0.00)***	(0.21)	(0,00)***	(0.00)***	(0.00)***
GTR_changes$_{(t)}$	+	0.1206	0.1352	0.0926	0.0993	0.1028	0.1105	0.1398	0.1405
		(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***
GTR_changes$_{(t-1)}$	+	0.0338		-0.0093		0.0034			
		(0.12)		(0.71)		(0.91)			
Stock_changes$_{(t)}$	-	-1.9618	-2.0118	-1.5027	-1.5058	-1.6523	-1.6656	-2.1183	-2.1220
		(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***
Stock_changes$_{(t)}$ x GTR_changes$_{(t)}$	-	-3.4598		-0.8889		-1.5054			
		(0.11)		(0.66)		(0.33)			
Stock_changes$_{(t)}$ x GTR_changes$_{(t-1)}$	-	-3.2075	-4.3030	-3.7950	-3.6266	-3.6301	-3.7408	-4.1490	-4.2142
		(0.04)**	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***
ρ [AR(1) coeff.]	+/-							-0.1654	-0.1675
								(0.00)***	(0.00)***
Country Effects		no	no	yes	no	yes	no	no	yes
Time Effects		no	no	yes	yes	yes	yes	no	no
R^2		35.71%	35.33%	55.77%	56.53%	34.90%	34.55%	34.27%	36.09%
F Test		86.09***	140.53***	13.87***	17.33***	38.52***	63.72***	113.21***	28.04***
Durbin-Watson stat.		2.35	2.33	2.76	2.75	2.65	2.28	2.03	2.03
N =(ixT)		767	767	767	767	767	767	754	754
Specification tests									
Cross section F-test (pooled OLS vs. FEM) p-value		(0.99)	(0.99)						
Period F-test (pooled OLS vs. FEM) p-value		(0.00)***	(0.00)***						
Hausman test (FEM vs REM)					(0.08)*				
Period Random									
Test of cross-sectional independence by Frees				(0.00)***					
Modified Wald test for group wise heteroskedasticity				(0.00)***					

Notes: This table presents the estimation results for the pooled, fixed and random effects models regarding Equation (1) for the period from 02 January 2020 to 09 April 2020.

P-values are in parentheses. ***,**** and ***indicate statistical significance at the 10%, 5%, and 1% level respectively. This note also applies in Table 4.

Table 3 Variance decomposition results for PVAR basic model

Response variable and forecast horizon	Impulse variable		
	GTR_changes	Stock_changes	Vix_changes
GTR_changes			
1	100.00%	0.00%	0.00%
2	99.62%	0.25%	0.13%
3	99.61%	0.26%	0.13%
Stock_changes_			
1	1.69%	98.31%	0.00%
2	2.07%	97.26%	0.67%
3	2.08%	97.21%	0.71%
Vix_changes			
1	2.73%	28.24%	69.03%
2	3.33%	27.69%	68.98%
3	3.35%	27.66%	68.98%

Notes: This table reports the results from the variance decomposition analysis for the basic PVAR model. The first column presents the response variable and its forecast horizon. GTR_changes refers to changes of google trends metric about COVID-19. Vix_changes refers to changes of stock market implied volatility. Stock_changes refers to changes of stock market returns.

Table 4. Panel data estimation results for changes on stock market VIX in Europe vs. Asia

Dependent Variable								Vix_changes					
Independent Variables	Exp. Sign	Pooled with PCSE		Fixed Effects with PCSE		Random Effects with PCSE		Pooled OLS with PCSE and AR(1)	Pooled OLS with PCSE and AR(1)	Fixed Effects with PCSE and AR(1)	Fixed Effects with PCSE and AR(1)		
Model		j=EUR	j=Asia	j=EUR	j=Asia	j=EUR	j=Asia	j=EUR	j=Asia	j=EUR	j=Asia		
C	+/-	0.0082	0.0082	0.0112	0.0111	0.0103	0.0103	0.0085	0.0084	0.0084	0.0084		
		(0.01)**	(0.01)**	(0.00)***	(0.00)***	(0.17)	(0,00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***		
D_j x GTR_changes$_{(t)}$	+	0.1640	0.0715	0.1115	0.0710	0.1244	0.0772	0.2525	0.1535	0.2519	0.1538		
		(0.00)***	(0.12)	(0.00)***	(0.07)*	(0.00)***	(0.04)**	(0.00)***	(0.04)**	(0.00)***	(0.04)**		
$(1-D_j)$ x GTR_changes$_{(t)}$	+	0.0931	0.1592	0.0744	0.1099	0.0846	0.1226	0.1921	0.2552	0.1913	0.2546		
		(0.01)**	(0.00)***	(0.04)**	(0.00)***	(0.01)**	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***		
D_j x Stock_changes$_{(t)}$	-	-2.1195	-2.2504	-1.5771	-1.7971	-1.7503	-1.9450	-2.1343	-2.2972	-2.1402	-2.3095		
		(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***		
$(1-D_j)$ x Stock_changes$_{(t)}$	-	-1.8588	-1.9269	-1.4287	-1.4051	-1.5704	-1.5670	-1.9396	-1.9720	-1.9431	-1.9745		
		(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***		
D_j x Stock_changes$_{(t)}$ x GTR_changes$_{(t-1)}$	-	-5.4529	-3.5387	-3.9877	-3.7593	-4.2297	-3.7197	-4.7851	-2.6949	-4.9186	-2.8032		
		(0.00)***	(0.07)*	(0.02)**	(0.02)**	(0.01)**	(0.02)**	(0.00)***	(0.25)	(0.00)***	(0.23)		
$(1-D_j)$ x Stock_changes$_{(t)}$ x GTR_changes$_{(t-1)}$	-	-1.9794	-4.8256	-2.9839	-3.7633	-2.8230	-3.9512	-1.5600	-4.3682	-1.5504	-4.3790		
		(0.39)	(0.01)**	(0.14)	(0.03)**	(0.16)	(0.02)**	(0.55)	(0.01)**	(0.52)	(0.01)**		
ρ [AR(1) coeff.]	+/-							-0.1620	-0.1655	-0.1644	-0.1678		
								(0.00)***	(0.00)***	(0.00)***	(0.00)***		
Country Effects		no	no	no	no	no	no	no	no	yes	yes		
Time Effects		no	no	yes	yes	yes	yes	no	no	no	no		
R^2		35.60%	35.37%	56.45%	56.55%	34.99%	34.74%	38.19%	38.11%	37.32%	37.23%		
F Test		71.58***	70.88***	16.51***	16.58***	32.34***	32.30***	67.47***	67.2400	24.59***	24.51***		
Durbin-Watson stat.		2.32	2.33	2.74	2.75	2.28	2.28	2.06	2.06	2.06	2.06		
N =(ixT)		767	767	767	767	767	767	754	754	754	754		
Specification tests													
Cross section F-test (pooled OLS vs. FEM) p-value		(0.99)	(0.99)										
Period F-test (pooled OLS vs. FEM) p-value		(0.00)***	(0.00)***										
Hausman test (FEM vs REM) Period Random				(0.13)	(0.16)								
Test of cross-sectional independence by Frees				(0.00)***	(0.00)***								
Modified Wald test for group wise heteroskedasticity				(0.00)***	(0.00)***								

Note: P-values are in parentheses. *,** and ***indicate statistical significance at the 10%, 5%, and 1% level respectively.

Table 5. Variance decomposition results for PVAR (European vs. non-European regions)

Response variable and Forecast horizon	Impulse variable			
European vs. Non-European Markets	GTR_changes_EUR	GTR_changes_ Ex EUR	Stock_changes	Vix_changes
Stock_changes				
1	1.46%	0.40%	98.14%	0.00%
2	1.84%	0.44%	97.08%	0.63%
3	1.86%	0.44%	97.03%	0.67%
Vix_changes				
1	2.24%	0.67%	28.15%	68.94%
2	2.48%	1.03%	27.60%	68.89%
3	2.49%	1.05%	27.58%	68.88%

Notes: This table reports the results for the European vs. non European markets by implementing the variance decomposition analysis for the basic PVAR model. The first column presents the response variable and its forecast horizon.GTR_changes_EUR refers to google trends metric for European markets and GTR_changes_Ex EUR for non-European markets (the rest markets in our sample). Vix_changes refers to changes of stock market implied volatility. Stock_changes refers to changes of stock market returns.

Table 6. Variance decomposition results for PVAR (Asian vs. non-Asian regions)

| Response variable and Forecast horizon	Impulse variable			
Asian vs Non-Asian Markets	GTR_changes_ASIA	GTR_changes_ Ex ASIA	Stock_changes	Vix_changes
Stock_changes				
1	0.15%	1.77%	98.08%	0.00%
2	0.23%	2.06%	97.06%	0.65%
3	0.23%	2.07%	97.01%	0.69%
Vix_changes				
1	0.57%	2.24%	28.15%	69.04%
2	0.74%	2.65%	27.60%	69.00%
3	0.75%	2.67%	27.57%	69.00%

Notes: This table reports the results from the Asian vs. non Asian markets by implementing the variance decomposition analysis for the basic PVAR model. The first column presents the response variable and its forecast horizon. GTR_changes_ASIA refers to google trends metric for Asian markets and GTR_changes_ Ex ASIA for non-Asian markets (the rest markets in our sample). Vix_changes refers to changes of stock market implied volatility. Stock_changes refers to changes of stock market returns.

Table 7. Panel data estimation results for Google Trend metric on dynamic conditional correlation between VIX & Stock changes

| Dependent Variable		abs(correlation between Vix&Stock_changes)					
Independent Variables	**Exp. Sign**	**Pooled with PCSE and AR(1)**			**Fixed Effects with PCSE and AR(1)**		
Model		j=All	j=EUR	j=Asia	j=all	j=EUR	j=Asia
C	+/-	0.03349	0.0345	0.0348	0.097461	0.1008	0.0978
		(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.01)**	(0.01)**
Dj x GTR_changes$_{(t-1)}$	+	0.026026	0.0296	0.0462	0.019484	0.0229	0.0210
		(0.02)**	(0.00)***	(0.00)***	(0.02)**	(0.01)**	(0.20)
(1-Dj) x GTR_changes$_{(t-1)}$	+		0.0204	0.0222		0.0011	0.0191
			(0.23)	(0.04)**		(0.94)	(0.04)**
ρ_j [AR(1) coeff.]	+/-	0.955131	0.9550	0.9488	0.861368	0.9139	0.7969
		(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***
Country Effects		no	no	no	yes	yes	yes
R^2		92.45%	92.59%	92.58%	93.80%	94.80%	93.90%
F Test		4681.83***	394.23.25**	2392.78***	818.78***	881.25***	739.27***
Durbin-Watson stat.		2.13	2.14	2.14	2.03	2.04	2.04
N =(ixT)		767	767	767	767	767	767
Specification tests							
Cross section F-test (pooled OLS vs. FEM) p-value		(0.00)***	(0.00)***	(0.00)***			
Hausman test (FEM vs REM)					(0.00)***	(0.00)***	(0.00)***
Test of cross-sectional independence by Frees					(0.00)***	(0.00)***	(0.00)***
Modified Wald test for group wise heteroskedasticity					(0.00)***	(0.00)***	(0.00)***

Notes: This table presents the results for the relationship between Google Trend metric and the dynamic conditional correlation between VIX & Stock changes for three country groups (All, Europe, Asia). P-values are in parentheses. ***,**** and ***indicate statistical significance at the 10%, 5%, and 1% level respectively. The "abs" refers to the absolute values of the dynamic conditional correlation estimates from the estimated DCC-GARCH models.

Figure 1a. Google Trend on Coronavirus, Stock & Vix prices in European Countries
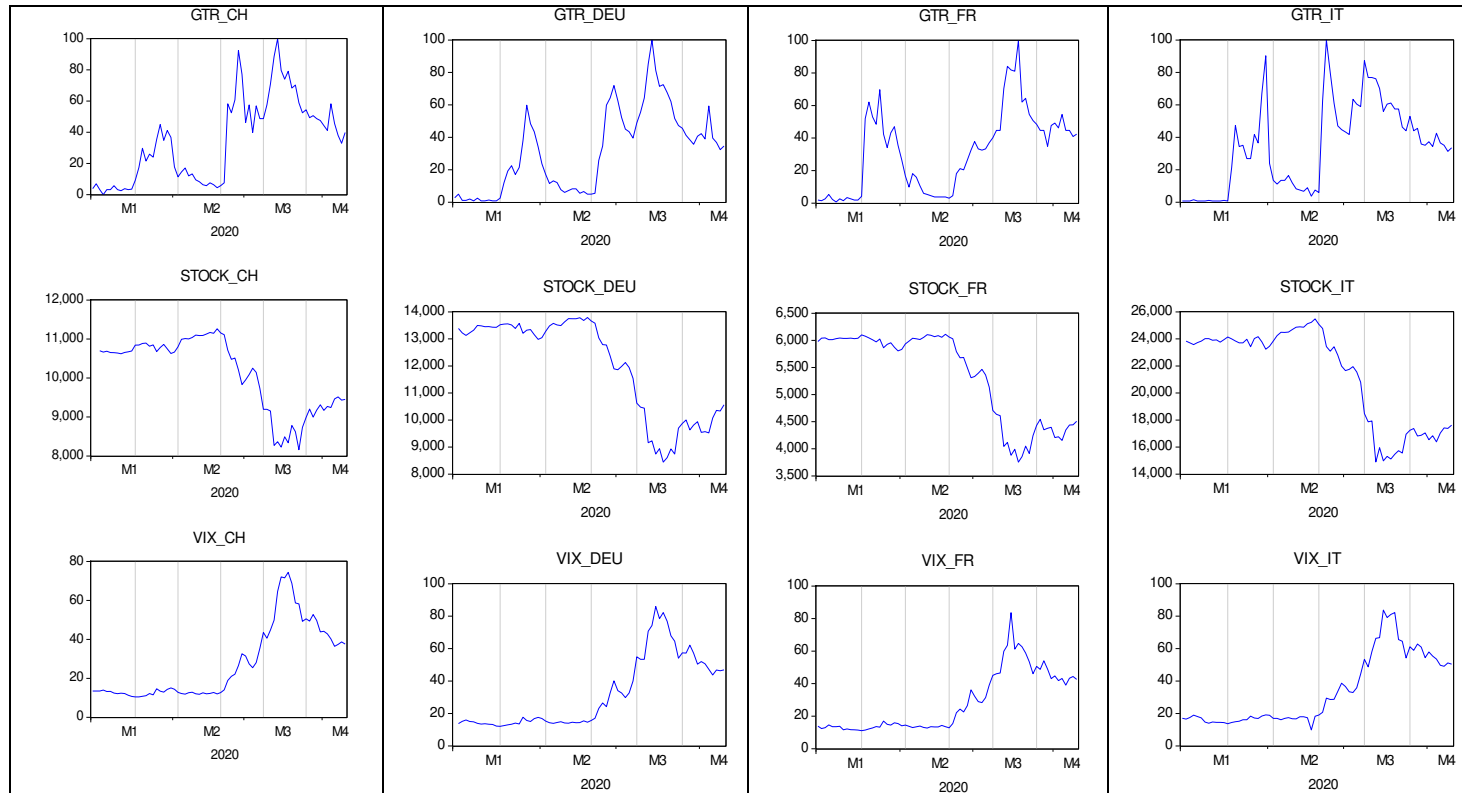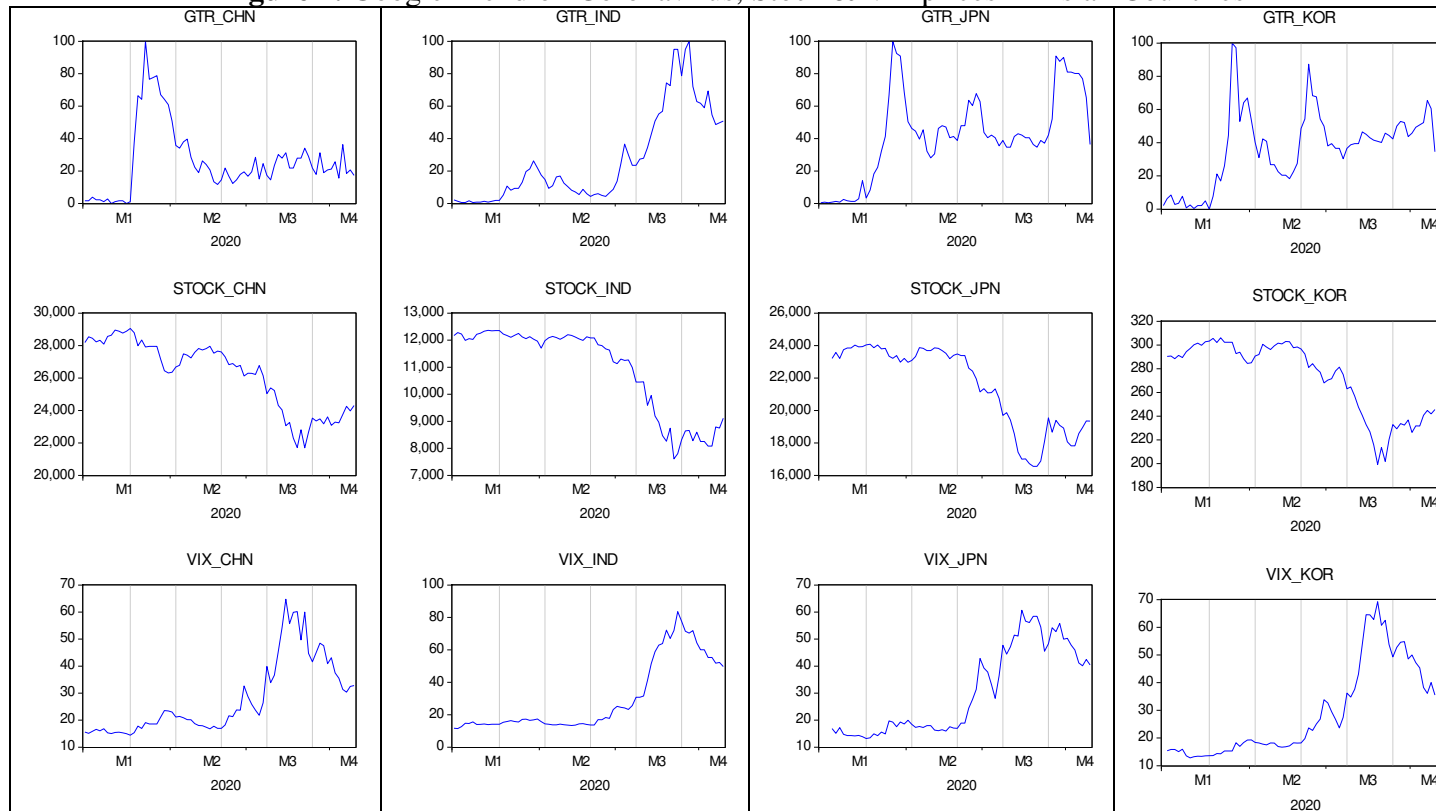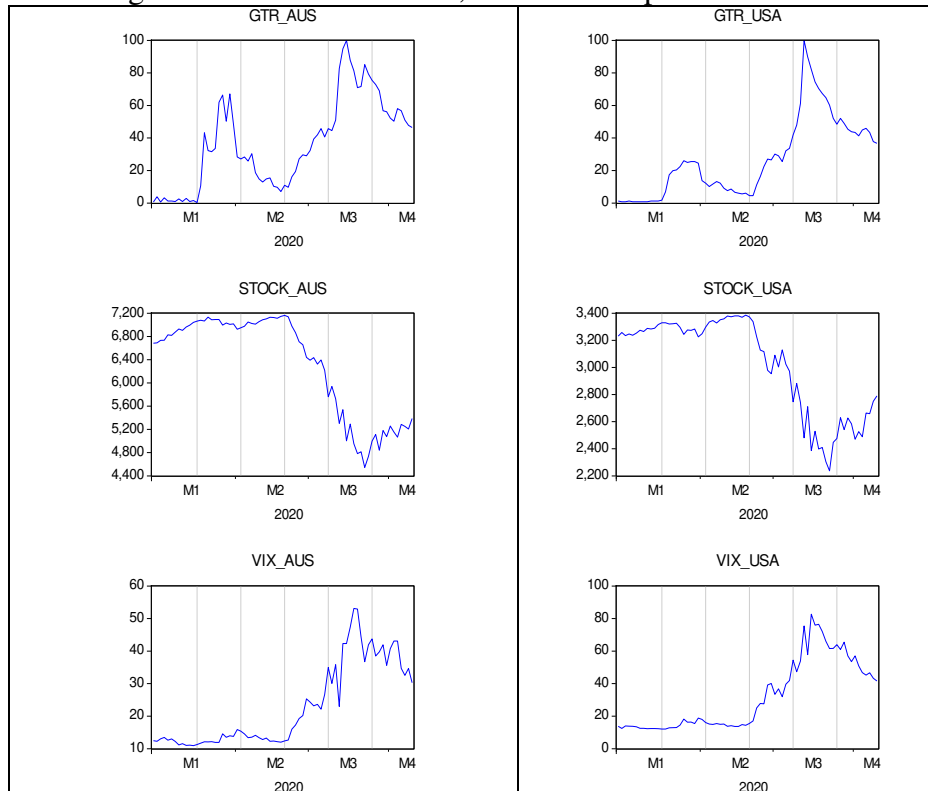

Note: GT: Google Trend on Coronavirus; Stock: stock prices of general index in each country; Vix: Implied Volatility index prices in each country; CH: Switzerland; DEU: Germany; FR: France; IT: Italy.

Figure 1b. Google Trend on Coronavirus, Stock & Vix prices in European Countries
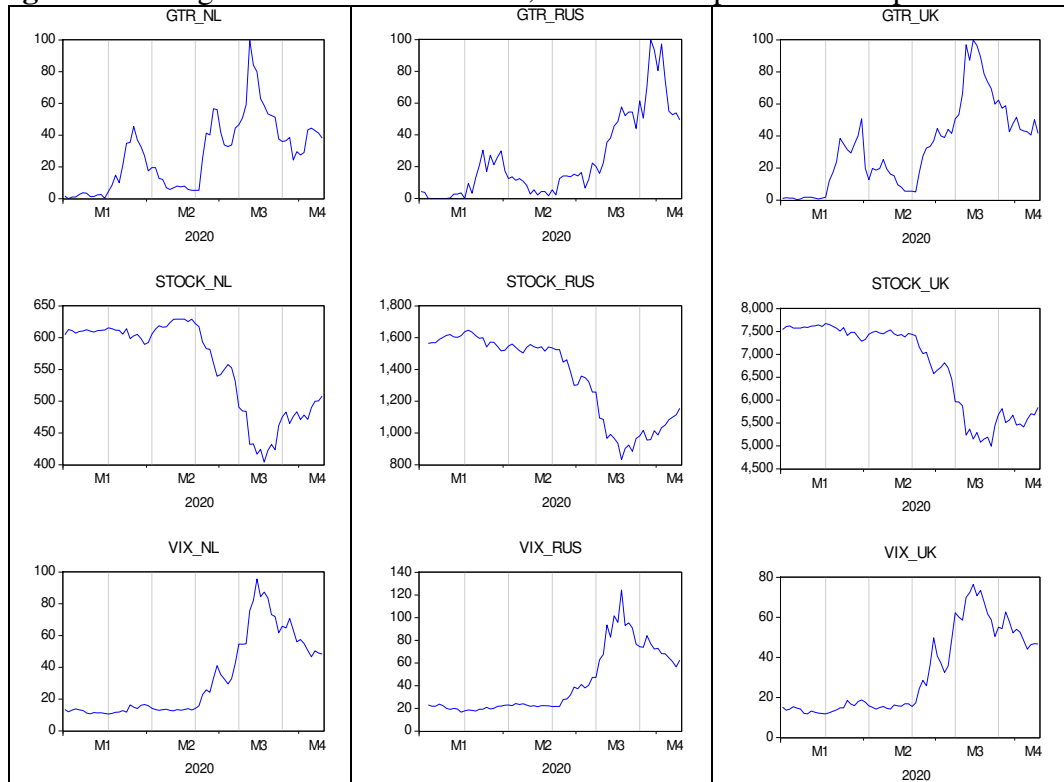
Note: GT: Google Trend on Coronavirus; Stock: stock prices of general index in each country; Vix: Implied Volatility index prices in each country; NL: Netherland; RUS: Russia: UK: United Kingdom.

Figure 2. Google Trend on Coronavirus, Stock & Vix prices in Asian Countries

Note: GT: Google Trend on Coronavirus; Stock: stock prices of general index in each country; Vix: Implied Volatility index prices in each country; CHN: China; IND: India; JPN: Japan; KOR: Korea.

Figure 3. Google Trend on Coronavirus, Stock & Vix prices in USA and Australia

Notes: GT: Google Trend on Coronavirus; Stock: stock prices of general index in each country; Vix: Implied Volatility index prices in each country; USA: United States; AUS: Australia.

Figure 4. DCC behavior over time
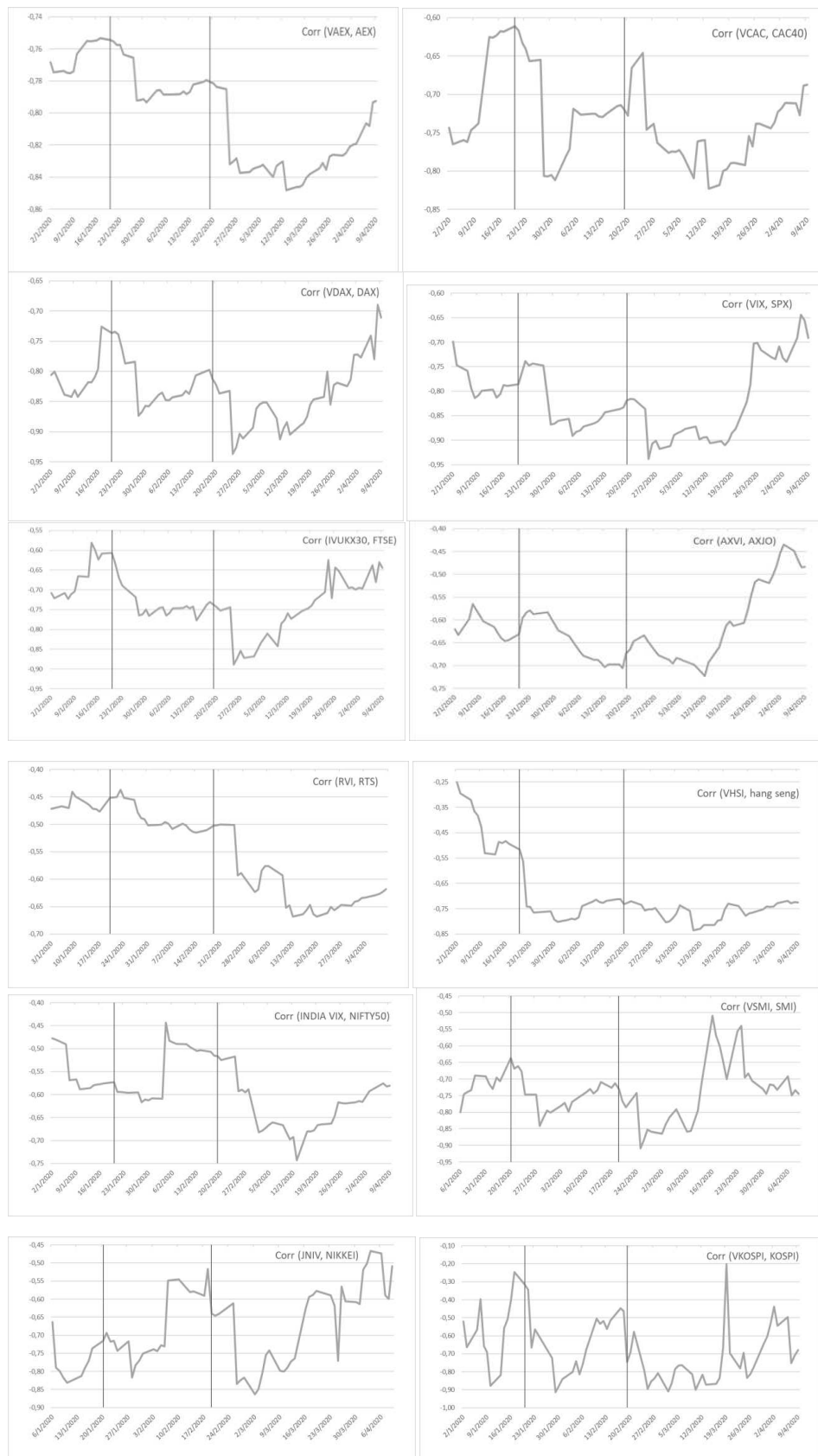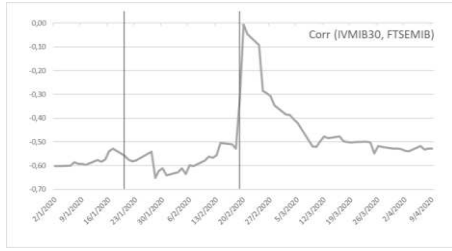
Notes: The vertical lines represent the following dates: 20/1/2020 and 19/2/2020. The abbreviations analyzed as follows. VAEX, AEX indicate the volatility and stock market indices of Netherland, respectively. VCAC, CAC40 indicate the French volatility and stock market indices, respectively. VDAX, DAX indicate the German volatility and stock market indices, respectively. VIX, SPX indicate the US volatility and stock market indices, respectively. IVUKX30, FTSE indicate the UK volatility and stock market indices, respectively. AXVI, AXJO indicate the Australia's volatility and stock market indices, respectively. RVI, RTS indicate the Russian volatility and stock market indices, respectively. VHSI, hang seng indicate the Hong Kong volatility and stock market indices, respectively. INDIA VIX, NIFTY50 indicate the Indian volatility and stock market indices, respectively. VSMI, SMI indicate the Switzerland's volatility and stock market indices, respectively. JNIV, NIKKEI indicate the Japanese volatility and stock market indices, respectively. VKOSPI, KOSPI indicate the Korean volatility and stock market indices, respectively. IVMIB30, FTSEMIB indicate the Italian volatility and stock market indices, respectively.

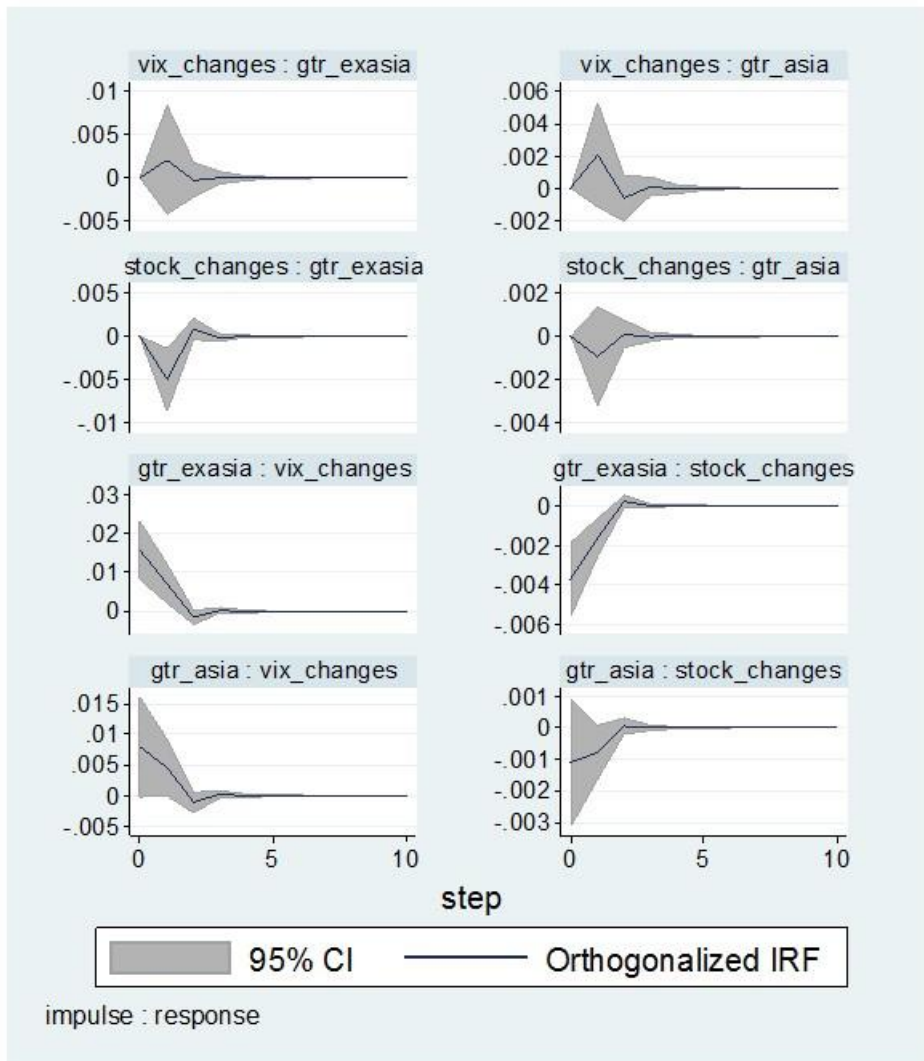**Figure 5.** Impulse response analysis for base PVAR model
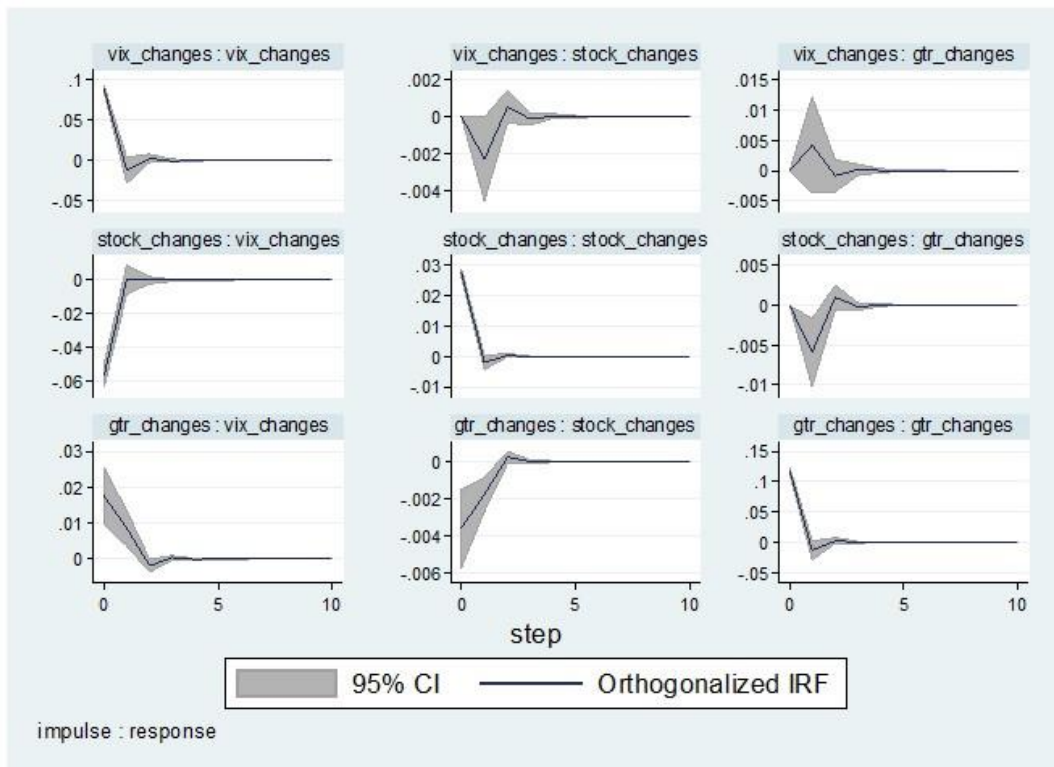
Notes: This figure depicts the impulse response analysis between stock returns (stock_changes) volatility indices changes (Vix_changes) and google trend metric (gtr_changes). The variable after symbol ":" is the variable that responds to the shock in variable before symbol ":".

Figure 6. Impulse response analysis for PVAR model on European vs non-European markets
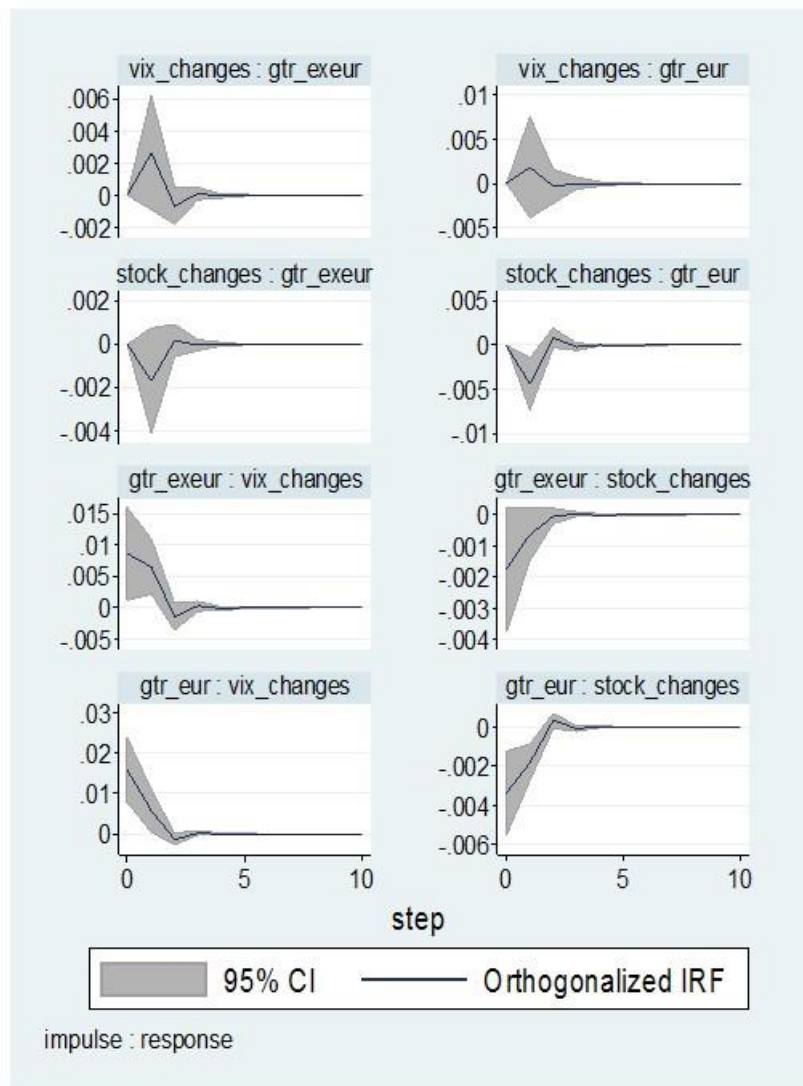
Notes: This figure depicts the impulse response analysis between stock returns (stock_changes), volatility indices changes (Vix_changes) and google trend metric (gtr_changes). gtr _eur refers to google trends metric on European markets and gtr_exeur on non-European markets (the rest markets in our sample). The variable after symbol ":" is the variable that responds to the shock in variable before symbol ":".

Figure 7. Impulse Response analysis for PVAR model on Asian vs non-Asian markets

Notes: This figure depicts the impulse response analysis between stock returns (stock_changes), volatility indices changes (Vix_changes) and google trend metric (gtr_changes). gtr_ASIA refers to google trends metric on Asian markets and gtr _ exasia on non-Asian markets (the rest markets in our sample). The variable after symbol ":" is the variable that responds to the shock in variable before symbol ":"