Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Political uncertainty, COVID-19 pandemic and stock market volatility transmission

George N. Apostolakis\textsuperscript{a}, Christos Floros\textsuperscript{a}, Konstantinos Gkillas\textsuperscript{b}, Mark Wohar\textsuperscript{c},* \\
\textsuperscript{a} Department of Accounting and Finance, School of Management and Economics Sciences (SEDO), Laboratory of Accounting and Financial Management – L.A.F.M, Hellenic Mediterranean University, Heraklion P.C 71500, Greece \\
\textsuperscript{b} Department of Management Science & Technology, University of Patras, Megalou Aleksandrou 1, Koukouli, Patras P.C 26334, Greece \\
\textsuperscript{c} College of Business Administration, University of Nebraska at Omaha, 6708 Pine Street, Omaha, NE 68182, USA

ARTICLE INFO

JEL classifications: 
C22 
C32 
C58 
G32 

Keywords: 
Asymmetric effects 
Volatility spillovers 
GARCH 
Volatility impulse responses 
Futures 
VECM

ABSTRACT

News about referendums and the ongoing evolution of a global contagious increase uncertainty about the development of economic fundamentals reflected by increased volatility in the financial markets. In this paper, employing volatility impulse response functions and assessing the volatility spillovers we examine intra-market volatility transmission in the Athens stock market. We employ a large sample period of daily data that spans from December 1999 to December 2020 and captures major events of the last 20 years especially related to the announcement of the two referendums during the Greek government-debt crisis in 2010 and the economic and political turmoil that increased country instability, the following years, the BREXIT referendum and the COVID-19 pandemic of 2020. Our results demonstrate that negative shocks during the announcement of the referendum produce larger impulse responses than during the announcement of the country lockdowns. Furthermore, we shed light on the existence of the dynamic relationship of volatility spillovers. Volatility spillovers peaked during the COVID-19 pandemic. Dynamic spillover plots demonstrate that during the COVID-19 pandemic, more volatility is transmitted by mid cap firms to large cap firms. Our findings have implications to market participants, policy makers and market regulators.

1. Introduction

The stock market of Greece has been not only the recipient of bad news and volatility spillovers stemming from the global financial markets but also was at the epicenter of the European Sovereign Debt Crisis (ESDC) of 2010. During that time period, two referendum announcements increased political instability and caused upset in the financial market. As the financial markets have become increasingly more integrated, global events such as the burst of dot com bubble, the sub-prime crisis and most recently the British referendum in 2016 and the COVID-19 pandemic increased uncertainty in the Greek financial markets.

Political uncertainty and macroeconomic news can influence financial market volatility (Albulescu, 2020; Onan et al., 2014). Several recent studies examine the effect of economic policy uncertainty on financial volatility (Antonakakis et al., 2019, 2013; Mei et al., 2018; Strobel et al., 2018; Su et al., 2019). A referendum, while it can be seen as a democratic process that reflects the willingness

* Corresponding author.

E-mail addresses: g.apostolakis@hmu.gr (G.N. Apostolakis), cfloros@hmu.gr (C. Floros), gillask@upatras.gr (K. Gkillas), mwohar@unomaha.edu (M. Wohar).

https://doi.org/10.1016/j.intfin.2021.101383
Received 2 February 2021; Accepted 11 July 2021
Available online 16 July 2021
1042-4431/© 2021 Elsevier B.V. All rights reserved.
of the society to decide on crucial dilemmas, their uncertain outcome can increase uncertainty in financial markets. Many studies examining the effect of referendums on financial markets exist in the literature (Beaulieu et al., 2006, 2006; Belke et al., 2018; Li, 2020). Limited research has been done on the announcements of the Greek referendums during the ESDC (Antonakakis et al., 2019; Hardouvelis et al., 2018).

News following the coronavirus outbreak were initially limited and focused in China and later Asia region. Soon, the gradual transformation from an epidemic to a pandemic increased uncertainty in financial markets as global economies slowed down due to the unprecedented governmental measures such as local lockdowns to restrict the infection of the population with this contagious virus. The literature examining the relation between a pandemic and financial markets is expanding quickly with new findings. Baker et al. (2020) quantify news of infectious disease outbreaks for over a century and find that stock market reaction to this latest pandemic was the most intensive in comparison with other ones due to how information rapidly circulates and is absorbed by markets. They posit that the current pandemic has a greater influence on US market volatility than the previous pandemics in 1918–19, 1957–58 and 1968 because of the more aggressive policy interventions to protect public health in a more service-oriented US economy than before. Several papers examine the relation between COVID-19 pandemic and financial markets (Ashraf, 2020; Azimli, 2020; Huynh, 2020; Huynh et al., 2021; Le et al., 2021; Singh, 2020; Zhang et al., 2020). Other scholars focus on the effects of the pandemic on market volatility (Albulescu, 2020; Bakas and Triantafyllou, 2020; Zaremba et al., 2020). Albulescu (2020) examining announcements of new cases of infection and fatality ratio find a positive effect on the financial market volatility. Bakas and Triantafyllou (2020) find support for a negative effect of pandemics on commodity volatility while Zaremba et al. (2020) in a similar vain to Baker they focus on policy intervention during the pandemic and find that stringent policy responses have a positive influence on stock return volatility.

In this study we contribute to the literature by examining volatility impulse responses of 3 different referendum announcements and compare them with those of COVID-19 restriction policy measures for the Greek markets. Secondly, we contribute to the literature by investigating volatility spillovers of stock returns between spot and futures markets and between large cap and medium firms during the last 20 years. Therefore, we focus our investigation on the events following the burst of the ESDC.

The remainder of the paper is organized as follows: After Section 2 and the literature review, Section 3 describes the methodology used in this paper and Section 4 presents the data, descriptive statistics and preliminary results, while the main empirical findings are presented and discussed in Section 5. Discussion and concluding remarks can be found in Section 6.

2. Literature review

According to the efficient market hypothesis (EMH) asset prices should reflect all relevant information available about their intrinsic value and therefore no arbitrage opportunities exist. However, due to market imperfections as Schwert (2003) postulates that information reaching to different markets may be asynchronous resulting in the existence of a lead-lag relationship. A vast amount of literature examines in scrutiny the lead-lag relationship between spot and future markets for several markets, using several different methods, and with the majority of them arguing that futures prices lead spot prices. In general, spot and future prices are considered to be cointegrated i.e. a long-run relationship exists although prices might deviate in the short-run. Market forces such as the opportunity for arbitrage should bring prices shortly back to equilibrium. Empirical studies employing a vector error correction model (VECM) reveal the existence of such a relationship in a unidirectional or a bi-directional form (Alemany et al., 2020; Arshanapalli et al., 1997; Chan et al., 1991; Pizzii et al., 1998; Tse, 1999; Wahab and Lashgari, 1993).

There is a growing number of studies focusing on the Greek capital markets, specifically testing the pricing efficiency and the price discovery process (Andreou and Pierides, 2008; Fassas, 2010; Fassas and Siriopoulos, 2019; Floros and Vougas, 2008; Kavussanos et al., 2008; Kavussanos and Visvikis, 2011; Kenourgios, 2005, 2004; Sogiakas and Karathanasis, 2015). Prior relevant studies find evidence of a long-run relationship between spot and futures markets. Futures markets are mainly price inefficient but are more information efficient than spot markets as information is incorporated faster in them, and that futures prices and volatilities primarily lead the respective spot markets.

In more detail, and from the early studies of the Greek markets, Kenourgios (2004) presents evidence of spillover effects in the mean spot and futures returns in the Greek market, but his findings show the presence of a bi-directional causality. In a following research, Kenourgios (2005) find support of market inefficiency for the Greek futures market. Kavussanos et al. (2008) posit that futures markets can be used as price discovery vehicles as information is disseminated faster than the stock market providing evidence of a bi-directional relationship between the two markets. The authors further explore volatility spillovers for the two markets and their findings reveal significant spillover effects from the futures markets to the spot market. In line with Kavussanos et al. (2008), Floros and Vougas (2008) argue that futures markets are informationally more efficient than underlying stock markets in Greece and play a price discovery role.

Andreou and Pierides (2008) test futures market price efficiency and find that mispricing factors such as transaction costs, anticipated volatility and time to maturity. In similar vain to Andreou and Pierides (2008), Fassas (2010) examines price efficiency and find that arbitrage opportunities exist in the future markets due to several factors such as futures maturity, dividends, volatility, liquidity and short-selling restrictions. Sogiakas and Karathanasis (2015), examining volatility spillovers between spot and derivatives markets in three European markets, find time varying spillover effect from derivatives to spot markets and that futures yields Granger-cause spot yields. Finally, in a recent study Fassas and Siriopoulos (2019) find strong evidence of price efficiency for the futures markets as the futures market leads the spot market and strong bi-directional dependence in the both markets volatility. Our study provides additional evidence on the lead lag relationship and the existence of spillover effects between the spot and futures markets employing a longer dataset from December 1999 to December 2020 while testing for the existence of structural breaks in the sample.
A second strand of literature examines intra-market volatility spillovers between large cap and small cap firms. Conrad et al. (1991) find that volatility shocks to large market value firms are important to the future dynamics of smaller firms returns, but shocks to smaller firms have no impact on the mean or the variance of the returns of larger cap firms. Kroner and Ng (1998) posit that negative return shocks stemming from large firms can cause volatility in the returns of small and large firms. Harris and Pisedtasalasai (2006) find a significant one-way volatility spillover effect from the portfolios of larger stocks to the portfolios of smaller stocks.

Empirical evidence examining cointegrating relationships with structural breaks and intra-market volatility spillovers between large and small firms is scarce. Miralles-Marcelo et al. (2013) and Pardo and Torró (2007) examine transmission of volatility in the Spanish capital market by analyzing the impulse-response function for conditional volatility. Pardo and Torró (2007) find volatility shocks coming from small companies is important to large companies, but only negative shocks stemming from large firms are important to small firms. Our aim is to detect the intensity of volatility shocks coming from large or small companies. While Miralles-Marcelo et al. (2013) find significant bi-directional relationships between the large, medium and small firms, these disappear when asymmetries and structural breaks are included in their analysis.

Regarding the Greek stock markets, Drakos (2016) investigate the lead–lag relationship between small and large capitalization stocks employing portfolio returns. He finds support that information is unidirectional from large-firm portfolios to small-firm portfolios for both the short-run and the long-run period. Our study differs from Drakos (2016) as we do not employ portfolio weights but market indices as in Pardo and Torró (2007). We contribute to the literature by examining the volatility spillovers employing an asymmetric multivariate BEKK-Multivariate-GARCH-X to check if each market can be used as a price discovery vehicle by market participants. The examination of volatility spillovers is important to understand the price discovery price mechanism exist between the markets.

Using the frameworks of Hafner and Herwartz’s (2006, hereafter HH) and Diebold and Yilmaz, (2012, 2009, hereafter DY) we examine volatility impulse responses in scenarios of crisis events. We estimate the Volatility Impulse Responses (VIRF) calibrated at different points in time. Our model includes asymmetric effects applying a multivariate BEKK-Multivariate-GARCH-X model. Several studies have used the HH framework to study volatility transmission after a shock and examine contagion effects during crisis events (Allen et al., 2017; Belke et al., 2018; Eraslan and Menla Ali, 2018; Jin and An, 2016; Panopoulou and Pantelidis, 2009). Furthermore, the spillover index of DY captures the transmission of volatility to and from markets in a static and dynamic form. Although there is abundant literature about the international spillovers using the DY connectedness framework, evidence of the spillover transmission between futures and spot markets and between Large and Mid-cap firms is scarce (Antonakakis et al., 2016; Magkonis and Tsouknidis, 2017). Antonakakis et al. (2016) explore dynamic volatility spillovers between the spot and futures markets using the DY framework. They conclude that volatility spillovers are two-way and affected by crisis events such as the global financial crisis (GFC) and the European Debt Crisis (EDC). Magkonis and Tsouknidis (2017) find evidence of time-varying spillovers among the spot-futures volatilities and across petroleum-based commodities in pairwise analysis. Finally, Allen et al. (2017) employing both the HH and the DY frameworks explore VIRFs and volatility spillovers among global markets. They find support for larger shocks dominating but shorter in duration when they include asymmetric effects into their model.

This study departs from previous studies and makes several contributions to the literature in the following ways. First, we present the results of VIRFs analysis for 4 specific historical events, incorporating asymmetries in our BEKK-MGARCH-X model and using the HH framework. Our aim is to analyze the transmission of shocks across markets capturing possible asymmetries in the volatility transmission mechanism. Several studies have previously studied the lead-lag structure and the existence of spillovers in the Greek markets. We additionally contribute to the literature by examining the response and the dynamics of volatilities and covariances to different shocks. Second, we examine dynamic spillover effects between the spot and futures markets and intra-market volatility spillover effects between large and medium size firms to determine their level of interdependence.

The first two events are linked to the EDSC burst in Greece (November 2011 and August 2015) and the political uncertainty that followed. In May 2010, the EU debt event triggered with the announcement of the €110 billion bailout program for Greece to avoid the economic collapse. Riots and tough negotiations between the Greek government and the troika led the prime minister at the time to announce an unexpected referendum. The second event is related to the political instability in Greece in 2015 and the following political events (elections and referendum). The Athens stock exchange closed on 27 June 2015 and reopened on 3 August 2015. The other two events that we aim to compare the volatility impulse responses from the Greek referendums shock are the BREXIT referendum on June 2016 and the Coronavirus restriction measures announcements on March 2020.

We can summarize our finding in the following aspects: We find the existence of a long-run relationship between the spot and future markets. Conversely, we do not find support for such a relationship when we examine stock returns of large and medium size firms, using a model with GARCH errors. In addition, we find that negative shocks coming from futures and small firms is important to spot and large firm returns, accordingly. VIRFs analysis showed that negative shocks are larger and longer in duration than those coming from positive shocks when we examined at a specific point in time. Finally, we find that the spot and futures volatility spillovers are mainly of bidirectional nature on average and dynamically time-specific by using the DY framework. Our findings are intended to provide insight to investors, financial analysts and forecasters, risk managers and financial regulators and market participants in the Greek financial market.

3. Econometric methodology and analysis strategy

3.1. Stationarity and cointegration tests

To determine the existence of a long-run relationship we perform unit root, cointegration and causality tests. A preliminary step is
to determine whether the series are weakly stationary, and their order of integration. To determine whether the data are stationary we conduct the ADF and the PP unit root tests. Next, we allow for structural breaks and we examine for unit roots with the Lee and Strazich (2003) test.

To examine break points in variance, we conduct the iterated cumulative sum of squares (ICSS) test, which endogenously detects the number and position of break points in the variance of series. Let $\epsilon_t$ denotes an uncorrelated random variable with mean zero and unconditional variance $h_t$. The test statistic is defined as:

$$ IT = \sup_k \sqrt{T/2} D_k $$

where $D_k$ is the centred CSS function $(C_k/C_T) - (k/T)$, $k = 1, \ldots, T$ and $C_k$ is the cumulative sum of squares of $\epsilon_t \sum_{t=1}^k \epsilon^2_t$. The value of $k$ that maximises $\sqrt{T/2} D_k$ is the estimate of the break date. A modified and generalized IT test proposed by Sansó et al. (2004) deal with conditional heteroskedasticity issues.

To test for cointegration we use the Johansen’s (1988) framework that estimates a vector error-correction model (VECM) with an unrestricted constant, allowing for linear trends in series but not in the cointegrating relations. The two test statistics under this framework are the $\lambda_{\text{trace}}(r)$ and the $\lambda_{\text{max}}(r, r + 1)$ where $\lambda$ denotes the eigenvalues and $r$ is the number of cointegrating vectors. We extend our cointegration analysis taking into consideration the possibility of structural breaks in the series. We follow Johansen et al. (2000) to allow for multiple breaks in the linear trend and breaks. Finally, we report the Gregory and Hansen (1996) cointegration test allowing for a single break in the cointegrating vector.

### 3.2. The conditional mean equation

We follow Pardo and Torró (2007) econometric approach. First, the mean model follows a VEC model approach.

$$
\Delta S_t = \alpha_1 + \alpha_1 Z_{t-1} + \sum_{j=1}^{p} \beta_1 \Delta S_{t-j} + \sum_{j=1}^{p} c_1 \Delta F_{t-j} + \epsilon_{1,t} \\
\Delta F_t = \alpha_2 + \alpha_2 Z_{t-1} + \sum_{j=1}^{p} \beta_2 \Delta S_{t-j} + \sum_{j=1}^{p} c_2 \Delta F_{t-j} + \epsilon_{2,t}
$$

where $S_t$ and $F_t$ refer to the logarithm of the Spot and Forward prices respectively, $\Delta$ is the first differences lag operator, $z_{t-1}$ is the lagged error correction term of the cointegration relationship between $S_t$ and $F_t$. $\alpha_k$, $\beta_k$, and $c_k$ for $i = 1, 2$ and $j = 1, \ldots, p$ are the parameters to estimate, $\epsilon_t$ re the residuals, and $p$ is the lag of the VECM$^1$ estimated by Ordinary Least Squares. The $b_j$ and $c_{ij}$ coefficients capture the short-run relationship and $n_i$ are the error correction coefficients regarding the long-run relationship.

### 3.3. The conditional variance equation

Following Engle and Kroner (1995) and Kroner and Ng (1998), we can write the covariance model in the form of a BEKK-Multivariate-GARCH(1,1) model:

$$ H_t = (C)' C + (A)' (e_{t-1}\epsilon_{t-1}) A + (B)' H_{t-1} B, $$

and in the form of BEKK-A-MGARCH(1,1) model augmented with shift dummies and asymmetry is expressed as:

$$ H_t = (C + Ed)' (C + Ed) + (A)' (e_{t-1}\epsilon_{t-1}) A + (B)' H_{t-1} B + (\Gamma)' \eta_{t-1} \eta_{t-1}' \Gamma, $$

where $C = (C_1, \ldots, C_p)$ is an $2 \times 2$ triangular matrix, $A, Bandd$ are $2 \times 2$ coefficient matrices, $H_{t-1}$ is the $2 \times 2$ conditional covariance matrix $\epsilon_t$, and $\eta_t$ are $2 \times 1$ vectors of the shocks and the Glosten et al. (1993) dummies for capturing negative asymmetries from the shocks accordingly, $d_t$ is the dummy-regressor (denoting exogenous dummy variance shift) and $E$ is a lower triangular matrix. By replacing $CC$ of the standard BEKK-MGARCH(1,1) model of Eq.(3) with $(C + Ed)' (C + Ed)$ we enforce positive definiteness avoiding to increase variance due to the inclusion of dummy variables. The parameter matrix $\eta_t$ measure the asymmetric response to negative shocks while $\Gamma$, is defined as $\Gamma_1$ if $\Gamma_1$ is negative, and zero otherwise. The elements of $A$ capture the effects of shocks on volatility while the elements of B capture the effects of past conditional variances measuring the diagonal parameters of the effects of past own shocks and past volatility in both cases. We control for the GFC adding a shift dummy variable on June 2008.

### 3.4. Volatility spillovers

We employ the approach of Hafner and Herwartz (2006) to measure multivariate volatility impulse response (VIRF) analysis in order to explore the intra-market transmission of shocks to return prices. This approach has been implemented by other scholars to examine VIRFs at specific points in time (Allen et al., 2017; Fengler and Herwartz, 2018; Li and Giles, 2015). In our empirical analysis of spot and forward markets and large and medium cap firms, we consider two historical events: 1) November 2011 and the

---

$^1$ Lags of the VEC and VAR models are estimated by minimizing the BIC and HQ criteria.
and the close of the Athens stock exchange for several days.

According to Hafner and Herwartz (2006) the conditional covariance matrix $\Sigma_t$ is a function of the innovations $\xi_t, \ldots, \xi_{t-p}$, the initial shock $z_0$ and $\Sigma_0$. VRF are now defined as the expectation of volatility conditional on an initial shock and history, subtracted by the baseline expectation that only conditions on history,

$$V_t(z_0) = E[vech(\Sigma_t)|\xi_{t-1}] - [vech(\Sigma_t)|\xi_{t-1}],$$

where $V_t(z_0)$ is an N-dimensional vector. The BEKK model is then transformed in its VCHC representation so as to generate volatility impulse response functions defined as the expectation of volatility conditional on initial shock and history minus the expectation conditional only upon history:

$$Vech(V_{i+1}) = Avech(e_i e_i'-H), \quad Vech(V_{i+k}) = (A + B)vech(V_{i+k-1}),$$

where $H_t$ is the covariance matrix, previously estimated by Eq. (4), at time t. Because our BEKK model includes asymmetry, we estimate VRFs by employing simulation methods.

Finally, we estimate the volatility spillover index and volatility spillover plots as in Diebold and Yilmaz (2012, 2009). They have developed a spillover index based on VAR model and variance decompositions where their 2012 spillover index is invariant to variable ordering by using generalized impulse response functions. We use the estimated conditional volatility from the BEKK-A-M–GARCH model for the same period giving a total of 5488 observations. After estimating a 2 variable stationary VAR(p) model of

$$\sum_{j=0}^{\infty} A_j e_t = \sum_{j=0}^{\infty} B_j e_{t-j} + \varepsilon_t,$$

where

$$\sum_{j=0}^{\infty} A_j e_t = \sum_{j=0}^{\infty} B_j e_{t-j} + \varepsilon_t,$$

and $\Sigma_0$ and $\varepsilon_t$ are the variance matrix of the vector of errors $\varepsilon$, the standard deviation of the error term for the $i$th equation and $\varepsilon_t$ is the selection vector with one as the $i$th element and zero otherwise. Given that they have used generalized impulse response functions the sum of the elements of each row of the variance decomposition table is not equal to 1. For the construction of the spillover index normalize each entry of the variance decomposition matrix by the row sum.

$$\Theta_{ij}^g(H) = \frac{\sigma_{ij}}{\sum_{i,j=1}^{N} \sigma_{ij}}(\varepsilon_i A_{0j} \sum \varepsilon_j)^2.$$

where $\Sigma$, $\sigma_{ij}$ and $\varepsilon_t$ are the variance matrix of the vector of errors $\varepsilon$, the standard deviation of the error term for the $i$th equation and $\varepsilon_t$ is the selection vector with one as the $i$th element and zero otherwise. Given that they have used generalized impulse response functions the sum of the elements of each row of the variance decomposition table is not equal to 1. For the construction of the spillover index normalize each entry of the variance decomposition matrix by the row sum.

$$\sum_{i,j=1}^{N} \Theta_{ij}^g(H) = 1$$

where $\sum_{i,j=1}^{N} \Theta_{ij}^g(H) = N$. The total volatility spillover index is then defined as

$$S^t(H) = \frac{\sum_{i,j=1}^{N} \Theta_{ij}^g(H)}{\sum_{i,j=1}^{N} \Theta_{ij}^g(H)} \times 100 = \frac{\sum_{i,j=1}^{N} \Theta_{ij}^g(H)}{N} \times 100$$

The directional volatility spillover measure of $S_{ij}$ received by market i from other markets j the directional volatility spillovers transmitted $S_{ij}$ by market i to market j, and the net spillovers $NS_{ij}$ are the difference between the shocks transmitted to and the shocks received from are computed as:

$$\sum_{i,j=1}^{N} S_{ij}(H) = \frac{\sum_{i,j=1}^{N} \Theta_{ij}^g(H)}{\sum_{i,j=1}^{N} \Theta_{ij}^g(H)} \times 100 = \frac{\sum_{i,j=1}^{N} \Theta_{ij}^g(H)}{N} \times 100$$

$$\sum_{j,i=1}^{N} S_{ij}(H) = \frac{\sum_{j,i=1}^{N} \Theta_{ij}^g(H)}{\sum_{j,i=1}^{N} \Theta_{ij}^g(H)} \times 100 = \frac{\sum_{j,i=1}^{N} \Theta_{ij}^g(H)}{N} \times 100$$

$$NS_{ij}(H) = S_{ij}(H) - S_{ji}(H)$$

4. Data and preliminary results

For the purpose of our analysis, we use daily stock market data from December 1999 to December 2020 for the Greek stock market; Futures 20, FTSE Large Cap and FTSE Mid Cap. The FTSE/Athex Large cap index and the FTSE/ATHEX Mid Cap Index comprise the top 25 companies and the medium-sized companies ranked by market capitalization, accordingly. Pardo and Torró (2007) postulate that
using stock indices has clear advantages over using portfolios because it results in direct signaling and reduced costs for implementing trading rules. The data were sourced from DataStream. We transform daily series to normalized logs starting from zero point.

Table 1 presents summary statistics. The sample mean of all series is negative. The Jarque-Bera (JB), kurtosis and skewness statistics indicate that the series are not normally distributed. High correlation between the series is evident. The series present serial correlation and ARCH effects, according to the Ljung-Box Q and the Engle tests. Unit root hypothesis is tested using the augmented Dickey-Fuller (ADF). The ADF and the PP unit root tests indicate whether the series are stationary. From the results as reported in Table 1, the non-unit root proposition was rejected for all series under observation and we conclude that all the series are non-stationary at level I(1). The above results of non-stationary are enhanced by the Lee and Strazicich (2003) unit root test where we allow changes in level and trends.

| Panel A | Athens Futures | Athens Spot | Mid-Cap | Athens Futures Return | Athens Spot Return | Mid-Cap Return |
|---------|----------------|-------------|---------|----------------------|-------------------|--------------|
| Mean    | −147.480       | −144.386    | −175.850| −0.049               | −0.048            | −0.041       |
| St. Dev. | 99.074         | 99.241      | 68.873  | 2.167                | 2.049             | 1.856        |
| Skewness| −0.048         | −0.052      | 0.376   | −0.188               | −0.305            | −0.630       |
| Kurtosis(excess) | −1.537     | −1.541      | −0.826  | 10.624               | 7.778             | 7.780        |
| Jarque-Bera | 541.95***    | 545.41***   | 285.06***| 25836.82***          | 13915.06***       | 14201.97***  |
| Maximum | 12.508         | 12.357      | 12.105  | 7.782                | 7.368             | 7.368        |
| Minimum | −318.275       | −315.219    | −311.129| −23.775              | −17.878           | −18.183      |
| L-B (50) | 188390.85***   | 188390.85***| 128413.96***| 44.105              | 57.822           | 73.684**     |
| ARCH (1–10) | 34.654***    | 56.405***   | 44.95***| 35.014***            | 56.760***         | 47.099***    |
| McLeod-Li (10–0) | 619.48***   | 1154.61***  | 812.89***| 625.63***            | 1163.58***        | 879.42***    |
| ADF     | −1.0474        | −1.0399     | −2.4391 | −72.209***           | −69.35***         | −66.97***    |
| PP      | −1.6861        | −1.6256     | −2.2084 | −72.1809***          | −69.3268***       | −67.434***   |
| LS      | −3.1354        | −3.1034     | −3.0721 | −38.0395***          | −68.8753***       | −31.0425***  |

Panel B

| Model 1 | Model 2 |
|---------|---------|
| Johansen CT | R = 0   | R = 1   |
|          | 127.627*** | 1.069  |
|          | 17.135**  | 0.624   |

| Model 1 | Model 2 |
|---------|---------|
| Johansen (2000) CT with breaks and shift dummies | R = 0   | R = 1   |
|          | 146.456*** | 10.533*** |
|          | 29.675***  | 8.737*** |

| GH     | −11.928*** | −5.570*** |
|--------|------------|-----------|
| Covariance\Correlation Matrix log series | Covariance\Correlation Matrix log return series |
| Forward | 31564.4 | 0.99992   | 0.96405  | 4.69981 | 0.93538 | 0.78489 |
| Spot Large Cap | 31123.8 | 30694.2   | 0.96137  | 4.15709 | 4.20263 | 0.80784 |
| Spot Mid Cap | 32346.2 | 31808.6  | 35665.8  | 3.15922 | 3.07479 | 3.44718 |

Note: The sample size is 5488 observations spanning from 1999:12:08 To 2020:12:18. ADF is the Augmented Dickey-Fuller test statistic calculated with an intercept. PP is the Phillips-Perron unit root test with intercept and trend in the series. The LS test is the Lee-Strazicich Unit Root Test allowing for 2 breaks in trend and in level. The number of lags for the unit roots tests selected by the BIC criterion. Johansen cointegration test (CT) with unrestricted constant that allows for a linear trend in series. Johansen test includes seasonal dummies, impulse dummies at point 10 June 2015 (crash = 1) and 2 level shift dummies at 20 June 2008 (dto381 < 1) and 31 October 2012 (dto631 > = 1). Number of replications (N): 2500 Length of Random Walks (T): 400. GH is the Gregory and Hansen Cointegration Test with break and trend (Gregory and Hansen, 1996; Johansen, 1988; Johansen et al., 2000). *** Significance at the 1% level. ** Significance at the 5% level. * Significance at the 10% level.

Fig. 1. Daily log stock indices Athens Stock Exchange and Futures (Dec 2019–Dec 2020). Note: series normalized at the first date.

using stock indices has clear advantages over using portfolios because it results in direct signaling and reduced costs for implementing trading rules. The data were sourced from DataStream. We transform daily series to normalized logs starting from zero point.

Table 1 presents summary statistics. The sample mean of all series is negative. The Jarque-Bera (JB), kurtosis and skewness statistics indicate that the series are not normally distributed. High correlation between the series is evident. The series present serial correlation and ARCH effects, according to the Ljung-Box Q and the Engle tests. Unit root hypothesis is tested using the augmented Dickey-Fuller (ADF). The ADF and the PP unit root tests indicate whether the series are stationary. From the results as reported in Table 1, the non-unit root proposition was rejected for all series under observation and we conclude that all the series are non-stationary at level I(1). The above results of non-stationary are enhanced by the Lee and Strazicich (2003) unit root test where we allow changes in level and trends.

2 FTSE/ATHEX Large Cap - PRICE index, FTSE/ATHEX Mid Cap - price index, ADEX-FTSE/ASE-20 continuous - sett. price, ADEX-FTSE/ASE-20 cont. index - sett. price.
Fig. 1 reflects the temporal evolution of the series in logs and in returns. It shows the closely comovements between future and spot prices. It also evident that large cap and mid cap move closely together during the periods of 2000-2003 and 2008-2012 and 3 large spikes during the last 5 years.

The modified ICSS test finds several segments with statistically significant different variances at the conventional significance level of 0.05 with the last 3 breaks of the large cap series coinciding with the European debt crisis.

5. Empirical findings

5.1. Cointegration analysis

The non-stationary of the series preludes for a cointegrating relationship. Results show the existence of a cointegrating vector between future and spot prices. Comparing the trace statistic (127.627) with the corresponding critical value, we can conclude that the null hypothesis of no cointegrating vectors (r = 0) is convincingly rejected, while the null hypothesis of a single cointegrating vector cannot be rejected for the spot and futures series. The trace statistic (17.135) for the Large Cap and Mid Cap series of no cointegrating vector is rejected as well.

Next, we allow for structural breaks in the series following Johansen et al. (2000). We include seasonal dummies, two-level shift dummies (January 2008 and October 2012) and one-point dummy (June 2015). The critical values for the 2 structural breaks in levels are calculated with the use of bootstrap methods. For forward and spot series and for Large and Mid-Cap series we find enough we find evidence to reject the null hypothesis of Rank II = 0 and also to reject the following hypothesis that of Rank II = 1, at the conventional levels of 0.5 percent. Additionally, and to robust our cointegration analysis, we conduct the Gregory-Hansen cointegration test with a single break, which rejects the hypothesis of no-cointegration for the spot and future series and for the large and medium cap series in Table 1.4

5.2. Spillover analysis

5.2.1. Spot and future markets

First, we try to find a possible lead-lag relationship between the 2 series. In Panel A of Table 2, we can see that short-run causality is unidirectional from the spot to the futures market as the lagged future coefficients are significant in the spot equation but not the other way around, when we look at the mean equations. Regarding the long-run relationship, ECTs of both equations are negative and significant.

Next, we utilize the conditional volatilities from the estimated VECM(5)-BEKK MGARCH model in Table 2. Multivariate residual diagnostics for remaining ARCH effects and for serial correlation in the mean shows that the model fit well the data. The estimates of the model using t-distribution and asymmetries shows that the coefficients of volatility spillover effects are not significant. Only the lagged conditional variance of the spot market affects its own conditional variance (0.9239). However, all the asymmetry coefficients appear to be significant except the D(2,2) coefficient (–0.1148) depicting the impact of a negative shock on the spot prices. The D(1,1) coefficient depicts the impact of a negative shock on the spot prices on its own variance is positive and significant indicating a greater impact of negative shocks from positive shocks in variance. Additionally, from the cross-effect asymmetry coefficients, it appears a negative shock in the spot (futures) market has a significant impact on the futures (spot) market.

The above conclusion is verified from the causality tests in the mean and in variance equations of the VECM in Table 3. Regarding, testing the variance equation parameters, the joint test on all cross-effects and the asymmetry coefficients of the BEKK model are significant. The Wald test excluding all the non-diagonal elements of both A and B matrices is significant (8.723), and the block exclusion tests are significant for the futures variance (13.832) i.e. a shock to the spot market affects the variance of the futures series and for the spot variance. These results support the finding of a bidirectional spillover transmission from spot to futures markets and vice versa. Kavussanos et al. (2008) find that volatilities in the cash markets have no effect on the volatilities of futures markets, while Fassas and Siriopoulos (2019) find a bidirectional volatility transmission for these markets. Moreover, there exist significant spillover effects from the futures markets to the corresponding spot. Sogiakas and Karathanassis (2015) find partial evidence of a time varying spillover effect from derivatives to spot markets.

5.2.1.1. VIRFs of spot and futures. Plots of the VIRFs from the asymmetric BEKK MGARCH model are shown in Fig. 2. First, we examine the two referendums related to the Greek sovereign debt crisis and the political instability that followed and increased uncertainty in the Greek financial markets during 2010 and 2015. We estimate the VIRF impulse responses for November 2011, and for August 2015 using the variance at that historical point in time as the baseline.

After tough negotiations with the troika of Greece bailout conditions and the rescue program, the prime minister George A. Papandreou announced on 31/10/2011 a referendum to be held in order for the program and economic reforms and the austerity

3 Break points of large cap series: 2000:06:28, 2001:01:03, 2001:07:03, 2002:03:19, 2002:09:20, 2003:07:14, 2004:10:01, 2005:05:25, 2005:12:13, 2006:09:20, 2007:01:03, 2008:01:18, 2008:06:25, 2008:10:21, 2009:04:29, 2010:05:14, 2011:09:21, 2015:07:31, and for mid-cap series: 2001:01:05, 2002:07:19, 2005:11:16, 2008:09:25, 2010:05:03, 2011:08:05, 2012:11:16, 2014:10:13, 2017:05:09

4 For the rest of our analysis, we use the theoretical cointegration vector $z = s - f$ rather an estimated vector for the spot and futures markets analysis. For the Large cap – Mid cap analysis we use the estimated vector from the Johansen et al. (2000) cointegration analysis.
measures to receive public consensus. While it was the first referendum to be held in Greece since 1974, it received a negative response domestically and abroad and it was put off on November 4. Athens stock market experienced high volatility during that week amid political instability concerns. The second referendum announcement was on 25 of June of the bailout conditions and took place on 5 July 2015. The stock market closed on June 26 and reopened on August 3, where it plunged about 23%.

Table 2
Estimation results and diagnostics of VEC (5) BEKK MGARCH models with asymmetry.

| Panel A: Mean Model Coeff | T-stat | Variable Coeff | T-stat |
|---------------------------|--------|----------------|--------|
| (Spot) | | (Large Cap) | |
| D_Spot(1) | 0.0356 | 1.1830 | D_Large Cap(1) | 0.0929 |
| | | | | 6.9773*** |
| D_Spot(2) | -0.0047 | -0.1739 | D_Large Cap(2) | 0.0123 |
| | | | | 0.9099 |
| D_Spot(3) | -0.0108 | -0.3241 | D_Large Cap(3) | -0.0103 |
| | | | | -1.3786 |
| D_Spot(4) | -0.0259 | -1.2602 | D_Large Cap(4) | -0.0109 |
| | | | | -0.7376 |
| D_Forward(1) | 0.0518 | 1.7982* | D_Mid Cap(1) | 0.0066 |
| | | | | 0.0451 |
| D_Forward(2) | -0.0149 | -0.6632 | D_Mid Cap(2) | -0.0246 |
| | | | | -1.6807* |
| D_Forward(3) | 0.0225 | 0.6815 | D_Mid Cap(3) | 0.0237 |
| | | | | 3.7378*** |
| D_Forward(4) | 0.0186 | 0.9925 | D_Mid Cap(4) | 0.0094 |
| | | | | 0.6308 |
| Constant | -0.0957 | -1.8920* | Constant | 0.0135 |
| | | | | 0.2253 |
| ECI(1) | -0.0384 | -2.4787** | ECI(1) | -0.0014 |
| | | | | -0.0881 |

Mean Model (Forward) Mean Model (Mid Cap)

| Variable Coeff | T-stat | Variable Coeff | T-stat |
|----------------|--------|----------------|--------|
| D_Spot(1) | 0.4431 | 14.139*** | D_Large Cap(1) | 0.0526 |
| | | | | 4.8532*** |
| D_Spot(2) | 0.2164 | 7.7940*** | D_Large Cap(2) | 0.0118 |
| | | | | 1.0013 |
| D_Spot(3) | 0.1235 | 3.4162*** | D_Large Cap(3) | 0.0194 |
| | | | | 3.5714*** |
| D_Forward(1) | -0.0522 | -2.1876* | D_Large Cap(4) | -0.0024 |
| | | | | -0.2043 |
| D_Forward(2) | -0.0354 | -11.996*** | D_Mid Cap(1) | 0.0632 |
| | | | | 4.5252*** |
| D_Forward(3) | -0.0263 | -9.2760*** | D_Mid Cap(2) | 0.0003 |
| | | | | 0.0216 |
| D_Forward(4) | -0.1079 | -2.9670*** | D_Mid Cap(3) | 0.0191 |
| | | | | 2.6126*** |
| Constant | -0.3235 | -6.5118*** | Constant | -0.0140 |
| | | | | -0.2408 |
| ECI(1) | -0.1149 | -7.3845*** | ECI(1) | -0.0048 |
| | | | | -0.3172 |

Panel B: Variance Model

| Coeff | T-stat | Coeff | T-stat |
|-------|--------|-------|--------|
| C(1,1) | 0.3548 | 7.6695*** | C(1,1) | 0.2920 |
| | | | | 6.6210*** |
| C(2,1) | 0.3380 | 7.0894*** | C(2,1) | 0.2058 |
| | | | | 5.7368*** |
| C(2,2) | 0.0773 | 7.4126*** | C(2,2) | 0.0574 |
| | | | | 1.0538 |
| A(1,1) | 0.2067 | 8.1754*** | A(1,1) | 0.0007 |
| | | | | 0.0091 |
| A(1,2) | -0.1103 | -4.3540*** | A(1,2) | 0.0263 |
| | | | | 3.4674*** |
| A(2,1) | 0.0886 | 3.4206*** | A(2,1) | 0.2635 |
| | | | | 1.9530 |
| A(2,2) | 0.3751 | 14.0670*** | A(2,2) | 63.8911*** |
| | | | | 8.0713*** |
| B(1,1) | 0.9239 | 79.9165*** | B(1,1) | 0.0015 |
| | | | | -0.1418 |
| B(1,2) | 0.0010 | 0.0816 | B(1,2) | -0.0119 |
| | | | | -1.0116 |
| B(2,1) | 0.0091 | 0.8395 | B(2,1) | 0.0932 |
| | | | | 75.5258*** |
| B(2,2) | 0.9344 | 77.9838*** | B(2,2) | 0.2195 |
| | | | | 90.934 |
| D(1,1) | 0.4992 | 8.5099*** | D(1,1) | 0.0835 |
| | | | | 4.162 |
| D(1,2) | 0.3626 | 5.8143*** | D(1,2) | 0.0549 |
| | | | | -0.2732 |
| D(2,1) | -0.3165 | -6.0665*** | D(2,1) | -0.0549 |
| | | | | 0.2732 |
| D(2,2) | -0.1148 | -1.8898* | D(2,2) | 0.1558 |
| | | | | 0.8304 |
| DTO381(1,1) | -0.1208 | -4.2530 | DTO381(1,1) | -0.0760 |
| | | | | -2.7244*** |
| DTO381(2,1) | -0.1090 | -3.8334 | DTO381(2,1) | -0.0177 |
| | | | | -0.6442 |
| DTO381(2,2) | 0.0141 | 1.8864* | DTO381(2,2) | -0.0723 |
| | | | | -3.9897*** |

Notes: BEKK model with Heteroscedasticity/Misspecification Adjusted Standard Errors T-statistics are calculated using a robust estimate of the covariance matrix. dto381 < 1 if date = 20/6/2008. ARCH test is the Engle (1982) test on the squared residuals.

*** Significance at the 1% level.
** Significance at the 5% level.
* Significance at the 10% level.
Comparing the VIRFs for the November 2011, the initial responses are positive, scaled up to 7 for the spot and up to 9 for the futures variance before the effect of the shock gradually cancel out after 100 days, revealing that the impact of the 2011 shock was larger in the futures market. Contrasting the impulse responses with the shock during the second referendum announcement on August 2015, the initial responses are positive about 35 for the spot, and for the futures is little over 60, suggesting that the impact from a negative shock is again larger in the futures markets.

When we predict shocks without considering asymmetry effects, VIRFs follow a very similar pattern but are initially lower in magnitude. The VIRFs from the BEKK MGARCH model depicted in blue line, are lower in size than before for the 2011 shock. We observe that the highest difference between asymmetry and without asymmetry shocks in VIRFs is for the forward variance for the 2011 shock and for the spot variance for the 2015 shock. Interesting, responses of the futures variance reach initially a higher level than those of the spot variance. It looks that the futures market uncertainty reacted in greater degree than the spot markets to this historical shock.

Subsequent, we examine the 2 historical shocks in variance: the first comes from the international financial markets and is the BREXIT referendum on June 2016 and the second is related to the COVID-19 pandemic and the policy measure announcements such as the first lockdown and social distancing and other government restrictions on March 2020. The British referendum, in contrast to Greek lasted for a prolonged period since its announcement, while it held on 24 June 2016. The news created turbulence and uncertainty in all major European stock markets after Brexit vote together the ASE (Burdekin et al., 2018).

Table 3
Restriction Tests in Mean and in Variance Equations VEC(5) BEKK-A-MGARCH Model.

| Spot – Futures | Large Cap - Mid Cap |
|----------------|---------------------|
| X2 -> X1 causality F(5,*) = 18.027*** | F(5,*) = 7.398*** |
| X2 -> X1 causality F(5,*) = 103.660*** | F(5,*) = 9.803*** |
| BEKK asymmetry cross effect test (ex. non-diagonal elements of A, B and D matrices) F(6,*) = 9.015*** | F(6,*) = 2.935*** |
| Asymmetry test F(4,*) = 56.913*** | F(4,*) = 23.630*** |
| Test of Exogeneity in Mean of All Variables F(10,*) = 267.797*** | F(10,*) = 12.373*** |
| Wald Test of Diagonal BEKK (ex. non-diagonal elements of A and B matrices) F(4,*) = 8.723*** | F(4,*) = 2.839*** |
| Block Exclusion Test, X1 Variance A(2,1) B(2,1) F(2,*) = 12.3746*** | F(2,*) = 0.010 |
| BEKK asymmetry Block Exclusion Test, X1 Variance A(2,1) B(2,1) D(2,1) F(3,*) = 13.838*** | F(3,*) = 0.899 |
| BEKK asymmetry Block Exclusion Test, X2 Variance A(1,2) B(1,2) D(1,2) F(3,*) = 13.832*** | F(3,*) = 0.899 |

Note: *** Significance at the 1% level. ** Significance at the 5% level. * Significance at the 10% level.

Fig. 2. VIRFs to a shock, VECM(5) BEKK-MGARCH Forward and Spot prices. Note: Referendum announcements.
Regarding the COVID-19, the Greek government announced restrictions measures and a general lockdown from March 23 until May 4. On March 16, government announced that a 14-day quarantine upon arrival to the country for travelers and additionally all shops will remain closed increasing concerns about the evolution of the pandemic in Greece and increasing volatility in Greek markets. A general national lockdown was announced on March 22 to prevent the spread of the Coronavirus.

In Fig. 3 we can observe that negative responses to a shock in Brexit referendum are larger than those of the COVID-19 for the variances and the covariance. The initial responses of the spot variance and the covariance of the Brexit shock reached a similar level as in the Greek referendum shock of 2015. As previously, we observe a stronger reaction from the futures markets. When we check the 2 models, the differences of negative shocks are now smaller than previously.

5.2.1.2. Dynamic spillover index and plots of spot and futures.

Using the generalized VAR framework of DY and the estimated conditional volatilities for the BEKK-A-MGARCH model we compute the total spillover index and dynamic spillover plots for the spot and futures markets. According to Table 4, the total spillovers between spot and futures volatilities is around 48%, while the directional spillovers for each market are also around 48% with the Spot market to contribute little to futures volatility than the other way around. The results are similar to Antonakakis et al. (2016) who find that volatilities are equally informative.

Following the static analysis of the decomposition of the total volatility spillover index, the dynamic analysis using a 200-days rolling window and 10-days forecasts period we present the dynamic total, directional and net spillover indices in Figs. 4–6. The total spillover index fluctuates from a minimum 40.74 during the February 2003 to a maximum of 49.68 achieved in November 2020 and during the COVID-19 pandemic and the second policy restriction announcements.
In Fig. 5, the directional dynamic spillovers are almost flat between 34.98 and 53.02 for the estimated time period for the spot market and similarly from 33.98 to 53.62 for the futures market. Positive values of the net spillover index indicate that the spot volatility is a net transmitter and futures volatility is a net receiver of spillovers. The net spillovers in Fig. 6 show that the spot market is a major net volatility receiver during the end of 2005 till the beginning of 2007. Futures spill most of the volatility to Spot market in March 2006. Notably, futures markets are net volatility receiver from the spot market during the 2015 and 2016 referendums and alter to net transmitters during the COVID-19 pandemic. The plot however does not provide clear-cut evidence which market leads the spillovers to the other market.

5.2.2. Large and mid-cap markets

The coefficients of the mean equations of the VECM-GARCH model in the right side of Table 2 Panel A, indicate a bidirectional relationship between large and mid-cap returns. The result is verified by the causality test in Table 3. Regarding the long-run

![Fig. 5. Directional Spillover from others, VAR(1)-BEKK-MGARCH Spot/Forward Market.](image)

![Fig. 6. Net Spillovers Large Cap vs Mid Cap, VAR(1)-BEKK-MGARCH Spot/Forward Market.](image)

![Fig. 7. VIRFs to a shock VEC(5) BEKK-MGARCH model.](image)
relationship, both the ECT of the mid-cap and large cap equation is negative and not significant and can be considered weakly exogenous.\(^5\)

Next, we focus on the variance equation and the volatility spillovers between large and mid-cap firms. For instance, the coefficient estimates \(\alpha_{12}\) and \(\beta_{12}\) measures the extent the squared lagged residuals and the lagged conditional variance of the large cap market determines the conditional variance of the mid-cap market, accordingly. Results from Table 2 Panel B show that no spillovers from mid-cap to large cap stocks exist at conventional levels. Additionally, the asymmetry effects appear to be not significant as well. Results from the spillover tests verify that there is no evidence of volatility transmission from mid-size firms to large size firm prices and vice versa. For instance, the block exogeneity test (\(H_0: A(1,2) = B(1,2) = D(1,2) = 0\)) shows that a shock to large firms does not affect the mid cap variance (0.899). Regarding the causality tests in Table 3, we find that the cross effect coefficients of the BEKK model are significant for a joint Wald test (\(H_0: A(1,2) = A(2,1) = B(1,2) = B(2,1) = D(1,2) = D(2,1) = 0, (2.935)\)). Additionally, the joint test on all the asymmetry coefficients (\(H_0: D(1,1) = D(1,2) = D(2,1) = D(2,2) = 0\)) shows that asymmetry coefficients are significant (23.630).

5.2.2.1. VIRFs of large and mid-cap stock returns. The VIRFs from the asymmetric BEKK are calculated on the shock at that point in time and show the responses to negative market index price movements. Similarly, to the VIRFs analysis for the spot and futures markets, Fig. 7 depicts the responses to negative shocks at two different point in time. In general, responses are lower in 2011 than in 2015. In August 2015, both responses are positive, with the initial response of mid cap being similar in size (40) to large cap before gradually phase out. Looking at VIRFs ignoring the asymmetry effects, the duration of the shock is shorter and lower in size from when we include asymmetry. A positive shock has greater impact on large cap than in mid cap returns, while a negative shock creates similar in magnitude VIRFs.

In Fig. 8, we can compare the VIRFs from a shock during the Brexit referendum and the COVID-19 pandemic. As in spot and futures markets, volatility responses are larger after the referendum than the coronavirus pandemic. Furthermore, the impact on mid cap variance looks to be lower than in the large cap variance when we examine both shocks. The large cap market has a stronger reaction than the mid cap market stemming from both these negative shocks.

To robust our finding we include an 11 days event window as in (Hafner and Herwartz, 2006) and we calculate the VIRFs on a shock on March 2020 In Fig. A.1 and A.2 in the Appendix we can see the average VIRFs for the forward/spot and Large/Mid cap series during the COVID-19 event. The impact for the spot variance and the covariance is initially larger 5 days before the COVID-19 announcements, while the response of the futures variance is larger after the event. Regarding the COVID-19 shock to the variances and the covariance of the large cap and mid cap returns, Fig. A.2 documents that on average the pre-COVID-19 responses are initially larger than the post COVID-19 responses up to 15 days period. The increase in the pre-event variance is lower for the futures market returns and for the mid cap returns than in the spot market and large cap firm returns, accordingly.

5.2.2.2. Dynamic spillover index and plots of large mid cap stock returns. Table 5 shows the volatility spillovers of large and mid-cap returns in the Greek market. In particular, the large cap (mid cap) volatility is responsible for 43.1% (42.5%) of the forecast error variance of the mid cap (large cap) volatility. Volatility returns from large firms contribute slightly more to the volatility of medium

---

\(^5\) The VEC(5) model without the GARCH errors resulted in a negative and significant ECT coefficient for the mid-cap equation (−0.0731). Results of the VEC(5) models are available upon request.
size firms than the other way around. Shocks to large cap volatility returns explain 57.5% of its own variability, in the generalized forecast error decompositions, and the mid-cap volatility returns explain 56.9% of its own variability.

Specifically, Figs. 9–11 plot the time varying spillovers and provide further insights into volatility interdependencies in the Greek market between large and medium cap firms. The total volatility spillovers present a U-shaped curve during the period of 2017–2019. During that period and on 1 March 2015 volatility spillover reach a minimum around 17%. Again, we observe maximum spillovers during the first phase of coronavirus in Greece on March 2020. Similarly, directional spillovers presented in Fig. 10 peaked for large cap firms during COVID-19 pandemic. Of greater interest are the net spillovers between the two indices in Fig. 11, which show that only during the 2015 referendum large cap volatility is a net transmitter of shocks to the mid cap firms. In contrast, during the Brexit referendum and the COVID-19 pandemic, large cap firms are net volatility receivers from mid-cap firms.

To examine the influence of international spillovers to the Greek markets, we expand the DY model with the CBOE volatility index (VIX). Results in Tables A.1 and A.2, show that the directional volatility spillovers from VIX to other Greek markets is relatively small with the spot market and the large cap firms having slightly more spillovers from global uncertainty.

Table 5
Total volatility spillover index VAR(3) Model.

|                | Large Cap | Mid Cap | From Others |
|----------------|-----------|---------|-------------|
| Large Cap      | 57.46     | 42.54   | 42.5        |
| Mid Cap        | 43.13     | 56.87   | 43.1        |
| Contribution to others | 43.1     | 42.5   | 85.7        |
| Contribution including own | 100.6  | 99.4 | 42.80%      |
| Net            | 0.6       | -0.6    |             |

Note: Dynamic volatility spillovers estimated from a VAR (3) model. The \((i,j)^{th}\) value is the estimated contribution to the error variance in the 10-days-ahead forecasts of market i coming from innovations to market j.

Fig. 9. Total Spillover, VAR(3)-BEKK-MGARCH Large Cap Mid Cap.

Fig. 10. Directional Spillover from others, VAR(3)-BEKK-MGARCH Large Cap Mid Cap.

Fig. 11. Net Spillovers Large Cap vs Mid Cap, VAR(3)-BEKK-MGARCH Large Cap/Mid Cap.
Table A1
Total volatility spillover index VAR(5) Model.

|            | VIX     | Spot    | Forward | From Others |
|------------|---------|---------|---------|-------------|
| VIX        | 97.89   | 1.03    | 1.08    | 2.1         |
| Spot       | 2.01    | 51.47   | 46.51   | 48.5        |
| Forward    | 1.80    | 48.17   | 50.03   | 50.0        |
| Contribution to others | 3.8    | 49.2    | 47.6    | 100.6       |
| Contribution including own | 101.7  | 100.7   | 97.6    | 33.5%       |
| Net        | 1.7     | 0.7     | 0.4     | -2.4        |

Note: Dynamic volatility spillovers estimated from a VAR (6) model. The (i,j)th value is the estimated contribution to the error variance in the 10-days-ahead forecasts of index i coming from innovations to index j.

Table A2
Total volatility spillover index VAR(6) Model.

|            | VIX     | Large Cap | Mid Cap | From Others |
|------------|---------|-----------|---------|-------------|
| VIX        | 97.90   | 0.76      | 1.34    | 2.1         |
| Large Cap  | 1.50    | 56.30     | 42.20   | 43.7        |
| Mid Cap    | 1.09    | 41.57     | 57.34   | 42.7        |
| Contribution to others | 2.6    | 42.3    | 43.5    | 88.5        |
| Contribution including own | 100.5  | 98.6    | 100.9   | 29.5%       |
| Net        | 0.5     | -1.4     | 0.8     |             |

Note: Dynamic volatility spillovers estimated from a VAR (5) model. The (i,j)th value is the estimated contribution to the error variance in the 10-days-ahead forecasts of index i coming from innovations to index j.

Fig. A1. VIRFs to a shock, VECM(5) BEKK-MGARCH Forward and Spot prices. Note: 11 days event window: 5 days prior and 5 days after the event.

Fig. A2. VIRFs to a shock, VECM(5) BEKK-MGARCH Large Cap and Mid Cap prices. Note: 11 days event window: 5 days prior and 5 days after the event.
However, a closer look at net spillovers, shows that large volatility spillovers are evident from the futures market during the COVID-19 pandemic. In general, the COVID-19 pandemic indicates that volatility is transmitted from the GFC (2008) and the ESDC (2010) but net transmitters during the 2015 referendum. In addition, mid cap firms spill most of the volatility spillovers in the cash market during the 2015 referendum and BREXIT referendum, when we look at net spillovers.

We find evidence that spot markets lead prices but not the other way around. Regarding the lead-lag relationship between large and small cap firms we find evidence of a short run bidirectional relationship between large and mid-cap firms. Our findings are in line with Drakos (2016) who find a lead–lag effect between small and large size portfolios in the short- run for the Athens equity market.

Second, volatility spillover results from a multivariate VEC(5)-BEKK-(A)-MGARCH model, suggest that asymmetry and spillover cross effects are important for the spot and futures markets. Furthermore, we examine the impact of conditional volatility at specific dates considering particular shocks in history that reflect the Greece sovereign debt crisis and the political uncertainty reflected by referendum announcements. VIRFs quantify the impact of shock on expected conditional volatility.

By examining the VIRFs we are able to provide an answer on the strength and persistency of the volatility spillovers between the markets. The volatility impulse responses demonstrate a positive impact on the expected variances and covariances. The size of this impact is larger in June 2015 in the Greek markets and the second referendum announcement than the other referendum events and the COVID-19 pandemic announcement. The volatility impulse responses to a negative shock contributed more than a positive shock on the expected conditional variance in the Greek Capital markets. In general, we find that, negative shocks at specific point in time produce larger impulse responses when we introduce asymmetry effects in our models. Our results from the VIRF analysis revealed that volatility spillovers increase sharply in times of turbulence while illustrate that the futures markets react stronger to different shocks. Furthermore, responses from negative shocks are more persistent than those stemming from positive shocks.

Finally, we summarize our findings using the DY spillover framework as follows: The empirical results show that the spot and futures markets are interrelated by their volatilities. Spot and future volatilities are equally informative of the volatilities to the other market with shocks to each market having similar contributions to the other’s market. Our findings are in line to Antonakakis et al. (2016) who posit that these two markets have similar responses to the same new information, on average. We find evidence that spot markets spill volatility in the cash market during the 2015 referendum and BREXIT referendum, when we look at net spillovers. However, a closer look at net spillovers, shows that large volatility spillovers are evident from the futures market during the COVID-19 pandemic.

Regarding intra-market spillovers related to the size of the firm, large cap firms spill more volatility to mid-cap firms than the other way around, on average. Spillover plots show that large cap returns are net spillover receivers from mid-cap firms in several events like the GFC (2008) and the ESDC (2010) but net transmitters during the 2015 referendum. In addition, mid cap firms spill most of the volatility to large cap firms during the last COVID-19 pandemic. In general, the COVID-19 pandemic indicates that volatility is...
transmitted from medium size firm returns to the large cap and from futures market to the spot market.

The markets react differently to new information and spillovers change sign as market players rebalance their portfolios and change their hedging strategy. Therefore, there is no clear evidence which market lead the other regarding the spillover transmission. In line with Antonakakis et al. (2016) we argue that each market’s volatility leads spillovers to the other interchangeably. A possible future research avenue could be the examination of the variance decompositions and their spectral representation by extending the DY framework to account for asymmetric and frequency connectedness across various investment horizons (Barunik et al., 2016; Barunik and Kocenda, 2019; Huynh et al., 2020a, 2020b).

Our findings have important implications to policy makers and market regulators regarding market’s stability and volatility transmission. They are equally helpful to investors and other market participants for the formulation of efficient hedging strategies and improved risk policies on the basis of the examined market volatility characteristics.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

All persons who have made substantial contributions to the work reported in the manuscript (e.g., technical help, writing and editing assistance, general support), but who do not meet the criteria for authorship, are named in the Acknowledgements and have given us their written permission to be named. If we have not included an Acknowledgements, then that indicates that we have not received substantial contributions from non-authors.

Appendix. Robustness test

See Figs. A1–A3.

References

Albulescu, C.T., 2020. COVID-19 and the United States financial markets’ volatility. Finance Res. Lett. 101699 https://doi.org/10.1016/j.frl.2020.101699.
Alemayehu, N., Aragó, V., Salvador, E., 2020. Lead-lag relationship between spot and futures stock indexes: intraday data and regime-switching models. Int. Rev. Econ. Finance 68, 269–280. https://doi.org/10.1016/j.iref.2020.03.009.
Allen, D.E., McAler, M., Powell, R., Singh, A.K., 2017. Volatility spillover and multivariate volatility impulse response analysis of GFC news events. Appl. Econ. 49, 3246–3262. https://doi.org/10.1080/00036846.2016.1257210.
Andreou, P.C., Pierreides, Y.A., 2008. Empirical investigation of stock index futures market efficiency: the case of the Athens Derivatives Exchange. Eur. J. Finance 14, 211–223. https://doi.org/10.1016/j.ijforecast.2011.02.006.
Antonakakis, N., Chatziantoniou, I., Filis, G., 2013. Dynamic co-movements of stock market returns, implied volatility and policy uncertainty. Econ. Lett. 120, 87–92. https://doi.org/10.1016/j.econlet.2013.04.004.
Antonakakis, N., Floros, C., Kizys, R., 2016. Dynamic spillover effects in futures markets: UK and US evidence. Int. Rev. Financ. Anal. 48, 406–418. https://doi.org/10.1016/j.irfana.2015.03.008.
Antonakakis, N., Gabauer, D., Gupta, R., 2019. Greek economic policy uncertainty: does it matter for Europe? Evidence from a dynamic connectedness decomposition approach. Phys. Stat. Mech. Its Appl. 535, 122280 https://doi.org/10.1016/j.physa.2019.122280.
Arshanapalli, B., Dukas, J., Lang, L., 1997. Common volatility in the industrial structure of global capital markets. J. Int. Money Finance 16, 189–209.
Ashraf, B.N., 2020. Stock markets’ reaction to COVID-19: cases or fatalities? Res. Int. Bus. Finance 54, 101249. https://doi.org/10.1016/j.ribaf.2020.101249.
Azimli, A., 2020. The impact of COVID-19 on the degree of dependence and structure of risk-return relationship: a quantile regression approach. Finance Res. Lett. 36, 101648 https://doi.org/10.1016/j.frl.2020.101648.
Bakas, D., Triantafyllou, A., 2020. Commodity price volatility and the economic uncertainty of pandemics. Econ. Lett. 193, 109283 https://doi.org/10.1016/j.econlet.2020.109283.
Baker, S.R., Bloom, N., Davis, S.J., Sammon, M., Viratyosin, T., 2020. The unprecedented stock market reaction to COVID-19. Rev. Asset Pricing Stud. 10, 101648 https://doi.org/10.1016/j.rapsu.2020.101648.
Barunik, J., Kocenda, E., 2019. Total, Asymmetric and Frequency Connectedness Between Oil and Forex Markets (No. 7756), CESifo Working Paper Series, CESifo.
Barunik, J., Kocenda, E., Vácha, L., 2016. Asymmetric connectedness on the U.S. stock market: bad and good volatility spillovers. J. Financ. Mark. 27, 55–78. https://doi.org/10.1016/j.jfinmar.2015.09.003.
Beaulieu, M.-C., Coste, J.-C., Essaddam, N., 2006. Political uncertainty and stock market returns: evidence from the 1995 Quebec referendum. Can. J. Econ. Can. Économique 39, 621–642. https://doi.org/10.1111/j.0008-4085.2006.00363.x.
Belke, A., Dubova, I., Oosowski, T., 2018. Policy uncertainty and international financial markets: the case of Brexit. Appl. Econ. 50, 3752–3770. https://doi.org/10.1080/00036846.2018.1436152.
Burdekin, R.C.K., Hughson, E., Gu, J., 2018. A first look at Brexit and global equity markets. Appl. Econ. Lett. 25, 136–140. https://doi.org/10.1080/13504861.2017.1302057.
Chan, K., Chan, K.C., Karolyi, G.A., 1991. Intraday volatility in the stock index and stock index futures markets. Rev. Financ. Stud. 657–684.
Conrad, J., Goldekin, M.N., Kauf, G., 1991. Asymmetric predictability of conditional variances. Rev. Financ. Stud. 4, 597–622.
Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: predictive directional measurement of volatility spillovers. Int. J. Forecast. 28, 57–66. https://doi.org/10.1016/j.ijforecast.2011.02.006.
Diebold, F.X., Yilmaz, K., 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. Econ. J. 119, 158–171. https://doi.org/10.1111/j.1468-0297.2008.02208.x.

Drakos, A.A., 2016. Does the relationship between small and large portfolios’ returns confirm the lead-lag effect? Evidence from the Athens Stock Exchange. Res. Int. Bus. Finance 36, 546–561. https://doi.org/10.1016/j.ribuf.2015.05.002.

Engle, R.F., Ng, V.K., 1993. Measuring and testing the impact of news on volatility. J. Finance 48 (5), 1749–1777.

Engle, R.F., Kroner, K.F., 1995. Multivariate simultaneous generalized ARCH. Econ. Theory 11, 122–150. https://doi.org/10.1017/S0266466600009063.

Eraerlan, S., Menla Ali, F., 2018. Oil price shocks and stock return volatility: new evidence based on volatility impulse response analysis. Econ. Lett. 172, 59–62. https://doi.org/10.1016/j.econlet.2018.08.022.

Fassas, A., 2010. Mispricing in stock index futures markets—the case of Greece. Available SSRN 1873949.

Fassas, A.P., Siripoulos, C., 2019. Intraday price discovery and volatility spillovers in an emerging market. Int. Rev. Econ. Finance 59, 333–346. https://doi.org/10.1016/j iref.2019.09.008.

Fengler, M.R., Herwartz, H., 2018. Measuring spot variance spillovers when (co)variances are time-varying – the case of multivariate GARCH models. Oxf. Bull. Econ. Stat. 80, 135–159. https://doi.org/10.1111/ojbs.12191.

Floros, C., Vougas, D.V., 2008. The efficiency of Greek stock index futures market. Manag. Finance 34, 498–519.

Glosten, L.R., Jagannathan, R., Runkle, D.E., 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks (Staff Report No. 157). Federal Reserve Bank of Minneapolis.

Gregory, A., Hanson, B., 1996. Residual-based tests for cointegration in models with regime shifts. J. Econom. 70, 99–126.

Hafner, C., Herwartz, H., 2006. Volatility impulse responses for multivariate GARCH models: an exchange rate illustration. J. Int. Money Finance 25, 719–740.

Hardouvelis, G.A., Karalas, G., Karanastasis, D., Samartzis, P., 2018. Economic Policy Uncertainty, Political Uncertainty and the Greek Economic Crisis (SSRN Scholarly Paper No. ID 315372). Social Science Research Network, Rochester, NY. Doi: 10.2139/ssrn.315372.

Harris, R.D.F., Pisedtasalasai, A., 2020. Return and volatility spillovers between large and small stocks in the UK. J. Bus. Finance Account. 33, 1556–1571. https://doi.org/10.1111/j.1468-5956.2006.00635.x.

Huynh, T.L.D., Hille, E., Nasir, M.A., 2020a. Diversification in the age of the 4th industrial revolution: the role of artificial intelligence, green bonds and cryptocurrencies. Technol. Forecast. Soc. Change 159, 120188. https://doi.org/10.1016/j.techfore.2020.120188.

Huynh, T.L.D., Nasir, M.A., Nguyen, D.K., 2020b. Spillovers and connectedness in foreign exchange markets: the role of trade policy uncertainty. Q. Rev. Econ. Finance 77, 102085. https://doi.org/10.1016/j.qref.2020.102085.

Ito, T., Engle, R.F., Lin, W., 1990. Where does the meteor shower come from? The role of stochastic policy coordination. NBER Working Paper, (w3504).

Jin, X., An, X., 2016. Global financial crisis and emerging market contagion: a volatility impulse response function approach. Res. Int. Bus. Finance 36, 179–195. https://doi.org/10.1016/j.ribuf.2015.09.019.

Johansen, S., 1988. Statistical analysis of cointegration vectors. J. Econ. Dyn. Control 12, 231–254.

Johansen, S., Mosconi, R., Nielsen, B., 2000. Cointegration analysis in the presence of structural breaks in the determinstic trend. Econom. J. 3, 216–249.

Kavussanos, M.G., Visvikis, I.D., 2011. The predictability of non-overlapping forecasts: evidence from a new market. Multinatl. Finace J. 15, 125–126.

Kroner, K.F., Ng, V.K., 1998. Modeling asymmetric comovements of asset returns. Rev. Financ. Stud. 11, 817–844. https://doi.org/10.1093/rfs/11.4.817.

Lee, J., Strazichich, M.C., 2005. Testing efficiency and the unbiasedness hypothesis of the emerging Greek futures market. Eur. Rev. Financ. Econ. 4, 3.

Li, Y., Giles, D.E., 2015. Modelling volatility spillover effects between developed stock markets and Asian emerging stock markets. Int. J. Finance Econ. 20, 155–177. https://doi.org/10.1002/ije.1506.

Magkonis, G., Tsoukridis, D.A., 2017. Dynamic spillover effects across petroleum spot and futures volatilities, trading volume and open interest. Int. Rev. Financ. Anal. 52, 104–118. https://doi.org/10.1016/j.ira.2017.05.005.

Mei, D., Zeng, Q., Zhang, Y., Hou, W., 2018. Does US Economic Policy Uncertainty matter for European stock markets volatility? Phys. Stat. Mech. Its Appl. 512, 221–222. https://doi.org/10.1016/j.physa.2018.08.019.

Miralles-Marcelo, J.L., Miralles-Quirós, J.L., Miralles-Quirós, M. del M., 2013. Multivariate GARCH models and risk minimizing portfolios: the importance of medium and small firms. Span. Rev. Financ. Econ. 11, 29–38. https://doi.org/10.15297/j.ferfe.2013.03.001.

Onan, M., Salih, A., Yasar, B., 2014. Impact of macroeconomic announcements on implied volatility slope of SPX options and VIX. Finance Res. Lett. 11, 454–462. https://doi.org/10.1016/j.frl.2014.07.006.

Panopoulou, E., Pantelidis, T., 2009. Integration at a cost: evidence from volatility impulse response functions. Appl. Financ. Econ. 19, 917–933. https://doi.org/10.1080/14662360903142655.

Pardo, A., Tornó, H., 2007. Trading with asymmetric volatility spillovers. J. Bus. Finance Account. 36, 1548–1566. https://doi.org/10.1111/j.1467-5957.2007.002029.x.

Pizzini, A., Economopoulou, A.J., O’Neill, H.M., 1998. An examination of the relationship between stock index cash and futures markets: a cointegration approach. J. Futur. Mark. 18, 99–107. https://doi.org/10.1002/1520-6523(199805)18:5<99::AID-FUT4>3.0.CO;2-N.

Sanzó, A., Aragó, V., Carrion, J.L., 2004. Testing for changes in the unconditional variance of financial time series. Span. Rev. Financ. Econ., DEA Working Papers 4, 32–53.

Schwert, G.W., 2003. Chapter 15 Anomalies and market efficiency. In: Handbook of the Economics of Finance, Financial Markets and Asset Pricing. Elsevier, pp. 929–974. https://doi.org/10.1016/S1574-0120(03)00524-0.

Singh, A., 2020. COVID-19 and safer investment bets. Finance Res. Lett. 36, 101528. https://doi.org/10.1016/j.frl.2020.101528.