Does Geopolitical Risks Predict Stock Returns and Volatility of Leading Defense Companies? Evidence from a Nonparametric Approach

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Abstract

We use the *k*-th order nonparametric causality test at monthly frequency over the period of 1985:1 to 2016:06 to analyze whether geopolitical risks can predict movements in stock returns and volatility of twenty-four global defense firms. The nonparametric approach controls for the existing misspecification of a linear framework of causality, and hence, the mild evidence of causality obtained under the standard Granger tests cannot be relied upon. When we apply the nonparametric test, we find that there is no evidence of predictability of stock returns of these defense companies emanating from the geopolitical risk measure. However, the geopolitical risk index does predict realized volatility in 50 percent of the companies. Our results indicate that while global geopolitical events over a period of time is less likely to predict returns, such global risks are more inclined in affecting future risk profile of defense firms.

Keywords: Geopolitical risks, returns, volatility, defense firms.

JEL Codes: C22, G10.

1. Introduction

Financial market returns and its volatility (often associated with uncertainty) are among the most important indicators for practitioners, as its helps them in capital budgeting and portfolio management decisions as they directly reflect companies' financial health and future prospects (Poon and Granger, 2003; Rapach et al., 2008; Bekiros et al., 2016a). Whilst for academics, predictability of financial market movements, challenges the idea of market efficiency, and in turn, assists in building realistic asset pricing models (Rapach and Zhou, 2013). Hence, predicting

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financial market returns and volatility is of paramount importance to both practitioners and academics in finance. However, predicting financial market movements is highly challenging as it inherently incorporates stochastic as well as nonlinear components (Bekiros et al., 2016b). Understandably a wide array of linear, nonlinear and nonparametric predictive models with variety of predictors related to domestic and international financial, macroeconomic, institutional, behavioural, and financial and economic uncertainty have been used (see Aye et al., (2016) and Bekiros et al., (2016b) for a detailed literature reviews). Not surprisingly, the empirical evidence of predictability on returns and volatility is mixed.

In this regard, there is also a related literature that has analyzed the role of geopolitical type of news or events (for example, terror attacks) in predicting movements of financial market returns and volatility (see for example, Chen and Siems, 2004; Drakos, 2004, 2010; Eldor and Melnick, 2004; Hon et al., 2004; Johnston and Nedelescu, 2006; Chuliá et al., 2007; Abadie and Gardeazabal, 2008; Arin et al., 2008; Fernandez, 2008; Nikkinen et al., 2008; Barros and Gil-Alana, 2009; Nguyen and Enomoto, 2009; Gul et al., 2010; Karolyi and Martell, 2010; Kollias et al., 2010, 2011a, b, 2013a; Chesney et al., 2011; Suleman, 2012; Christofis et al., 2013; Aslam and Kang 2015; Apergis and Apergis, 2016; Balcilar et al., 2016a, b, forthcoming a; Gupta et al., 2016).[1] In sum researchers, find that not only geopolitical risks like domestic terror attacks, but also attacks on major financial markets, tend to affect both domestic stock returns and volatility (Balcilar et al., 2016b).

The economic intuition of geopolitical risks in driving financial markets is that portfolios that include stocks which are affected by such events are usually faced with a sudden and large increase in risk that cannot be diversified away. This in turn, results in large movements in the market due to reshuffling of portfolios, and also panic selling by investors in search for safer financial instruments, with this behavior continuing unless, investors' perception about a stable future is restored (Apergis and Apergis, 2016). In addition, geopolitical risks are believed to affect business cycles and financial markets, with geopolitical risks being often cited by central bankers, financial press and business investors as one of the determinants of investment decisions (Caldara and Iacoviello, 2016).

Against this backdrop, the objective of this paper is to analyze the role played by geopolitical risks in predicting movements in stock returns and volatility of the major players in the global

[1] Note some studies have also used either dummy variables or time-varying approaches to relate to periods of geopolitical tensions to analyze spillovers between oil and stock markets (see for example, Kollias *et al.,* (2013b) and Antonakakis *et al.,* (2014) and references cited therein).

defense industry. The unstable climate caused by geopolitical risks cause investors to expect increased dividends from the defense industry. Geopolitical events tend to serve as a learning mechanism for investors and risk managers, with them re-assessing the risk component in their portfolios. As investors expect future geopolitical risks, they aim to minimize the drastic impact on their portfolio by investing in industries which are already stable and strong, to provide them with a sense of stability and safety by directing human sentiments away from the effects of fear and insecurity associated with such events (Kis-katos et al., 2011; Ciner et al., 2013). In addition, there are also expectations of a stronger demand for military equipment deals by countries who are highly succeptible to geopolitical risks and events, and also from those nations who plan to undertake military action against threats of such risks (Akerman and Seim, 2014).

For our purpose, we use the k-th order nonparametric causality test of Nishiyama et al. (2011) at monthly frequency over the period of 1985:1 to 2016:06. This test is developed to incorporate higher-order interrelationships inherently based on a nonlinear dependence structure between the investigated variables in question, i.e., between returns and squared returns (with the latter measuring volatility) and geopolitical risks. Besides squared returns to capture volatility, we also use measure of realized volatility, given that we have daily data on the stock prices of the major global defense firms. Our decision to use a nonparametric approach, besides accounting for predictability in returns and volatility, also controls for any possible misspecification of a linear framework of causality, which is likely to (and as we show does) exist in the relationship between stock returns of the defense firms vis-à-vis geopolitical events.

Our measure of geopolitical risks and events is based on the recently developed news-based index of geopolitical risks by Caldara and Iacoviello (2016). This index is broad measure of global uncertainty, as it includes not only terror attacks but also other forms of geopolitical tensions like war risks, military threats, Middle East tensions. More specifically, such an index allows us to capture geopolitical risks of various forms all over the world in a continuous fashion, and allows us to go beyond the effect of specific events in a specific country at a specific point in time. Given the global nature of the defense industries under consideration, we believe that this index allows us to provide a more realistic picture of the impact of geopolitical risks on stock returns and volatility of the defense-related firms due to various forms of such global risks.

In the process, we can look beyond the event-study based approach of Apergis and Apergis (2016), whereby the authors analyzed the impact of the November 13th, 2015, Paris terrorist attacks on the stock returns of the most important companies in the global defense industry. This paper reported an upward trend in cumulative abnormal returns across all companies over the post-attack period, suggesting a positive effect of the attacks on the defensive companies' stock returns. Our paper can thus be considered to be an extension of the work of Apergis and Apergis (2016) by analyzing not only the impact of the Paris terror attacks (an event included in the measurement of the index) on the behavior of the equities of the leading defense companies, but also many other such geopolitically risky events that have taken place over the period of 1985 to 2016. While, the role of geopolitical risks in affecting aggregate stock market movements of the BRICS (Brazil, Russia, India, China and South Africa) and the US have been analyzed by Balcilar et al., (2016b), and Caldara and Iacoviello (2016) respectively; but to the best of our knowledge, this is the first attempt to analyze the impact of geopolitical risks on stock returns and volatility of defense companies.

As pointed out by Apergis and Apergis (2016), analysing the impact of geopolitical risks n defense companies is important since these firms perform an unique function of providing national governments with state-of-the-art equipment and services required for national security and also for carrying out their military missions. At the same time, these firms also leads the behaviour of the entire capital market, since in the wake of heightened geopolitical risks, such as terror attacks, it is expected that more market participants would be attracted given the role these firms play in the fight against terrorism. As argued by industry watchers, more and multiyear contracts are expected to positively affect a company's valuation by reducing the risk perception in the overall market. The remainder of the paper is organized as follows: Section 2 outlines the methodology, while Section 3 discusses the data. Section 4 presents the results of the predictability analysis for returns and volatility, with Section 5 concluding the paper.

2. Methodology

In this section, we briefly describe the methodology proposed by Nishiyama *et al.* (2011), with the test restricted to the case when the examined series follow a stationary nonlinear autoregressive process of order one under the null. Nishiyama *et al.* (2011) motivated the high-order causality by using the following nonlinear dependence between series

$$y_t = g(y_{t-1}) + \sigma(x_{t-1})\epsilon_t \tag{1}$$

where $\{y_t\}$ and $\{x_t\}$ are stationary time series (i.e., defense industry returns and the measure of geopolitical risks) and $g(.)$ and $\sigma(.)$ are unknown functions which satisfy certain conditions for stationarity. In general, x_{t-1} has information in predicting y_t^K for a given integer *K*. Consequently, the null hypothesis of non-causality in the K^{th} moment is given by

$$H_0: E(y_t^K | y_{t-1}, \dots, y_1, x_{t-1}, \dots, x_1) = E(y_t^K | y_{t-1}, \dots, y_1)\ w.p.1. \quad (2)$$

where $w.p.1$ is abbreviation for "with probability one". Formally, we say that x_t does not cause y_t up to the K^{th} moment if

$$H_0: E(y_t^K | y_{t-1}, \dots, y_1, x_{t-1}, \dots, y_1) = E(y_t^K | y_{t-1}, \dots, y_1)\ w.p.1. \quad \text{for all } k = 1, \dots, K \quad (3)$$

For $k = 1$, this definition reduces to non-causality in mean. Nishiyama *et al.* (2011) note that, it is easy to construct the test statistic $\hat{S}_t^{(k)}$ for each $k = 1, \dots, K$. We implement the test for $k = 1$ to test for causality in the 1st moment (non-causality in mean), and for $k = 2$ in the 2nd moment (non-causality in variance). The five percent critical value of the test statistic is 14.38.

Note that our geopolitical risk index is monthly, hence our causality tests must also be based on monthly returns and squared returns. However, given that we have daily data for stock indices of the defense firms, we are able to compute a measure of realized volatility, which in turn, allows us to check the robustness of our findings related to the measure of market volatility (squared returns). The measure that we consider is the classical estimator of realized volatility, i.e. the sum of squared daily returns (Andersen and Bollerslev, 1998), expressed as

$$RV_t = \sum_{i=1}^{M} y_{t,i}^2 \quad (4)$$

where $y_{t,i}$ is the daily $M \times 1$ return vector and $i = 1, \dots, M$ the number of daily returns.

3. Data

Monthly data on geopolitical risk (GPR) is obtained from the recent work of Caldara and Iacoviello (2016). This paper constructs the GPR index by counting the occurrence of words related to geopolitical tensions, derived from automated text-searches in leading 11 national and international newspapers. The authors look into the following newspapers: The Boston Globe, Chicago Tribune, The Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, Los Angeles Times, The New York Times, The Times, The Wall Street Journal, and The Washington Post. The index is constructed searching the electronic archives of each newspaper starting from January 1985 for eight phrases, namely: “geopolitical risk(s)", “geopolitical concern(s)", “geopolitical tension(s)", “geopolitical uncertainty(ies)", “war risk(s)" (or “risk(s) of war"), and “military threat(s)", “terrorist threat(s)", “terrorist act(s)", and “Middle East AND tensions". Based on these search criteria, Caladara and Iacoviello (2016) calculate the index by counting in each of the above-mentioned 11 newspapers, for each month, how many articles contain the search terms above. The index is then normalized to average a value of 100 in the 2000-2009 decade. The data on the GPR index are available for download from: https://www2.bc.edu/matteo-iacoviello/gpr.htm. We take logarithms of this data, and find it to be stationary in log-levels based on standard unit root tests.[2]

The data on daily closing stock prices of twenty-four global defense corporations listed on various stock markets were obtained from Bloomberg. The names of the companies and the period of data coverage for each of them have been listed in Table 1 of the paper. Daily returns were computed as percentage first differences of logged prices, which in turn, were used to compute the realized returns and realized volatility over a specific month based on the number of trading days. Table 2 summarizes the basic statistics of the GPR index and the realized stock returns and volatility of the various defense companies considered. As can be seen from the table, stating points of the sample differs based on data availability of either the stock price or the GPR index depending on whichever starts at a later date. The data however, ends in 2016:06 for all the twenty-four companies. Not surprisingly, stock returns of these companies depict negative skewness and excess kurtosis leading to the rejection of the null of normality in majority of the cases. The GPR index is non-normal only at the ten percent level of significance. The data for the stock returns and the log-level of the GPR index have been plotted in Figure 1.

[INSERT TABLES 1 and 2, and FIGURE 1]

4. Empirical Results

Though our objective is to analyse the *k*-th order causality running from the GPR index on stock returns and volatility of the twenty-four defense companies, for the sake of completeness and comparability, we also conducted the standard linear Granger causality test based on a VAR(1) model. The results have been reported in Table 3. The decision to use a model of order one is to be not only consistent with the lag-length choice of the Nishiyama et al., (2011) test, but also, we

[2] Complete detailes of the unit root tests are available upon request from the authors.

are in line with the stock returns predictability literature (see Rapach et al., 2005). As can be seen, barring two cases (Badcock International and Rockwell Collins) there is no evidence of causality running from GPR on stock returns of defense companies at the conventional 5 percent level of significance.

[INSERT TABLE 3]

Next, to motivate the use of the nonparametric causality approach, we statistically investigate the possibility of nonlinearity in the stock returns, and in its relationship with the measure of the geopolitical risk. To this end, we apply the Brock et al., (1996, BDS) test on the residuals of the stock returns equation in AR(1) models of stock returns and VAR(1) models of stock returns and the GPR. As reported in Tables 4a and 4b, the results provide ample evidence of the rejection of the null of *i.i.d.* residuals at various embedded dimensions (*m*), for all cases considered. These results provide strong evidence of nonlinearity in the data generating process of stock returns, as well as, in its relationship with the GPR. This means that, the results based on the linear Granger causality test cannot be deemed robust and reliable.

[INSERT TABLES 4a AND 4b]

Given the strong evidence of nonlinearity in stock returns and in the relationship between stock returns and GPR, we now turn our attention to the nonparametric *k*-th order test of causality. We make the following observations: First, there is no evidence of GPR in predicting stock returns in any of the twenty-four defense firms considered. So, unlike Apergis and Apergis (2016) who depicted the impact of the the 13th November, 2015 Paris terror attacks on stock returns, we do not find any evidence of geopolitical risks taken all together over a period of time. This result seems to suggest, that effect on returns is possibly event specific. Second, in two cases (General Dynamics and Northrop Grumman), we find evidence of GPR causing volatility as measured by squared returns. Finally, besides the above two companies squared returns of which are caused by GPR, there are 10 (BAE Systems, Boeing, Cobham, Elbit Systems, Harris Corporation, L3 Communications, Lockheed Martin, Rheinmetall, Rolls-Royce holding, and United Technologies) other companies, where we observe geopolitical risks to affect realized volatility. In other words, in 50 percent of the 24 companies, GPR is found to predict volatility, especially when measured by realized volatility.

[INSERT TABLE 5]

In sum, our results indicate that while geopolitical risk over a time frame is less likely to predict returns, the effect is more evident in the risk profile (volatility) of these defense firms, when we allow for nonlinearity. From a general perspective, we also highlight the importance of accounting for possible misspecifications in a linear model, which in turn, might lead to erroneous inferences.

5. Conclusions

There exists a literature which has shown that global geopolitical stock market returns and volatility. Against this backdrop, the objective of this paper is to analyze the role played by geopolitical risks in predicting movements in stock returns and volatility of twenty-four major companies in the global defense industry. For our purpose, we use the *k*-th order nonparametric causality test of Nishiyama et al., (2011) at monthly frequency over the period of 1985:1 to 2016:06. This test is developed to incorporate higher-order interrelationships inherently based on a nonlinear dependence structure between the investigated variables in question. Besides squared returns to capture volatility, we also use measure of realized volatility, given that we have daily data on the stock prices of the defense companies. Our decision to use a *k*-th order nonparametric approach, besides allowing us to for higher-order predictability, controls for the misspecification of a linear framework of causality, which as we show does exist in the data generating process of stocks returns and in its relationship with a measure of geopolitical risks. Hence, the mild evidence (two cases) of causality obtained under the linear Granger tests cannot be relied upon. When we apply the nonparametric test, we find that while there is no evidence of predictability of stock returns of these defense companies emanating from the geopolitical risk measure, the index does predict realized volatility in 50 percent of the companies. Hence, our results indicate that while global geopolitical events over a period of time (rather than at a specific point) is less likely to predict returns, with the effect more concentrated in changing the future risk profile of defense firms. In addition, from a general perspective, we also highlight the importance of modelling nonlinearity in causal relationships to avoid drawing incorrect conclusions. As part of future research, given that the stock returns depict skewed distributions, one could apply nonparametric quantiles-based test of causality as in Balcilar et al., (forthcoming b), which has an advantage over the conditional-mean based test of Nishiyama et al., (2011), in the sense that the causality-in-quantiles method covers the entire conditional distribution of stock returns and volatility. In addition, it would be interesting to see if our results hold over an out-of-sample period, since in-sample predictability (as conducted here), does not necessarily guarantee forecasting gains (Rapach and Zhou, 2013).

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Table 1: Defense companies and corresponding sample periods

Company	Stock Ticker in Bloomberg	Sample period
Badcock International	LON: BAB	1989:09 - 2016:06
BAE systems	LON: BA	1985:01 - 2016:06
Boeing	NYSE: BA	1985:01 - 2016:06
Booz Allen Hamilton	NYSE: BAH	2010:12 - 2016:06
Cobham	LON: COB	1985:01 - 2016:06
Elbit systems	TLV: ESLT	1998:07 - 2016:06
Esterline technologies	NYSE: ESL	1985:01 - 2016:06
General Dynamics	NYSE: GD	1985:01 - 2016:06
Harris corporation	NYSE: HRS	1985:01 - 2016:06
Huntington Ingalls	NYSE: HII	2011:04 - 2016:06
L3 communications	NYSE: LLL	1998:06 - 2016:06
Leidos Holdings Inc.	NYSE: LDOS	2006:11 - 2016:06
Lockheed Martin	NYSE: LMT.WD	1995:04 - 2016:06
Mantech International	NASDAQ: MANT	2002:03 - 2016:06
Northrop Grumman	NYSE: NOC	1985:01 - 2016:06
Orbital ATK	NYSE: OA	1990:11 - 2016:06
OSI systems	NASDAQ: OSIS	1997:11 - 2016:06
Raytheon	NYSE: RTN	1985:01 - 2016:06
Rheinmetall	ETR: RHM	1985:01 - 2016:06
Rockwell Collins	NYSE: COL	2001:07 - 2016:06
Rolls-Royce holding	LON: RR	1987:06 - 2016:06
Textron	NYSE: TXT	1985:01 - 2016:06
Ultra electronics	LON: ULE	1996:11 - 2016:06
United technologies	NYSE: UTX	1985:01 - 2016:06

Table 2: Summary statistics

Company	Mean	Median	Standard Deviation	Skewness	Kurtosis	Normality Test Jarque-Bera	*p*-value	N
Badcock International	0.004	0.01	0.104	-0.243	6.085	130.838	0.00	322
BAE systems	0.005	0.008	0.094	-0.918	7.717	403.474	0.00	378
Boeing	0.007	0.014	0.08	-0.941	5.617	163.639	0.00	378
Booz Allen Hamilton	0.006	-0.003	0.083	-0.153	4.232	4.503	0.105	67
Cobham	0.005	0.009	0.084	-0.544	5.062	85.621	0.00	378
Elbit systems	0.009	0.017	0.064	-0.289	4.351	19.426	0.00	216
Esterline technologies	0.004	0.011	0.114	-0.527	5.566	121.224	0.00	378
General Dynamics	0.007	0.01	0.073	-0.573	5.513	120.137	0.00	378
Harris corporation	0.007	0.014	0.086	-0.573	4.28	46.514	0.00	378
Huntington Ingalls	0.022	0.023	0.075	-0.068	3.587	0.954	0.62	63
L3 communications	0.011	0.013	0.075	-0.305	4.038	13.114	0.001	217
Leidos Holdings Inc.	- 0.001	-0.007	0.07	-0.291	4.999	20.942	0.00	116
Lockheed Martin	0.009	0.013	0.073	-1.702	11.739	934.565	0.00	255
Mantech International	0.004	0.007	0.093	-0.572	4.618	28.129	0.00	172
Northrop Grumman	0.007	0.013	0.085	-0.629	6.05	171.477	0.00	378
Orbital ATK	0.014	0.01	0.079	0.441	4.038	23.79	0.00	308
OSI systems	0.007	0.017	0.168	0.02	6.93	144.184	0.00	224
Raytheon	0.007	0.016	0.074	-1.375	11.659	1300.092	0.00	378
Rheinmetall	0.003	0	0.106	-0.042	5.456	95.129	0.00	378
Rockwell Collins	0.007	0.013	0.076	-1.022	6.442	120.198	0.00	180
Rolls-Royce holding	0.004	0.008	0.094	-0.86	6.77	249.641	0.00	349
Textron	0.006	0.014	0.105	-0.689	10.468	908.225	0.00	378
Ultra electronics	0.008	0.011	0.062	-0.207	3.586	5.057	0.08	236
United technologies	0.008	0.013	0.073	-1.515	11.032	1160.716	0.00	378
LNGPR	1.414	1.403	0.133	0.219	2.584	5.749	0.056	378

Note: The Jarque-Bera test has a null of normality and the *p*-value corresponds to the probability associated with the rejection of the null; N stands for number of observations; LNGPR is natural logarithms of the geopolitical risk index.

Table 3: Linear Granger causality test

Company	F-statistic
Badcock International	5.735*
BAE Systems	0.006
Boeing	0.942
Booz Allen Hamilton	0.687
Cobham	0.024
Elbit Systems	1.162
Esterline Technologies	0.15
General Dynamics	0.00
Harris Corporation	0.89
Huntington Ingalls	0.521
L3 Communications	0.057
Leidos Holdings Inc.	0.24
Lockheed Martin	0.064
Mantech International	0.048
Northrop Grumman	0.485
Orbital ATK	0.183
OSI Systems	0.377
Raytheon	0.252
Rheinmetall	0.00
Rockwell Collins	4.173*
Rolls-Royce holding	3.622
Textron	0.5
Ultra Electronics	0.126
United Technologies	0.581

Note: * indicates rejection of the null that geopolitical risk does not Granger cause stock returns of a specific defense company at 5 percent level of significance.

Table 4a: Brock et al.,'s (1996) BDS Test of nonlinearity on residuals for an AR (1) model of stock returns

Company	Dimension				
	2	3	4	5	6
Badcock International	2.789**	4.26***	5.339***	6.134***	6.968***
BAE Systems	1.782*	3.016***	3.543***	4.204***	4.809***
Boeing	1.22	1.492	2.739**	3.55***	4.371***
Booz Allen Hamilton	-2.192**	-4.874***	-2.48**	-1.577	-0.839
Cobham	2.488**	2.812**	2.162**	1.779*	2.332**
Elbit Systems	-7.251***	-3.65***	-7.544***	-4.639***	-3.055***
Esterline Technologies	1.646*	2.032**	2.473**	2.628**	2.753**
General Dynamics	5.694***	6.655***	7.383***	7.469***	7.734***
Harris Corporation	2.442**	3.13***	3.6***	3.864***	3.755***
Huntington Ingalls	3.228***	3.701***	3.988***	4.399***	4.281***
L3 Communications	1.699*	2.225**	2.297**	2.759**	2.965***
Leidos Holdings Inc.	1.683*	1.768*	1.494	0.398	-0.003
Lockheed Martin	4.382***	5.223***	6.404***	7.397***	8.179***
Mantech International	1.689*	1.674*	2.361**	2.8**	3.036***
Northrop Grumman	5.436***	6.11***	6.732***	7.582***	8.177***
Orbital ATK	0.723	1.835*	2.198**	2.652**	2.785**
OSI Systems	5.436***	6.11***	6.732***	7.582***	8.177***
Raytheon	3.713***	5.116***	5.627***	5.554***	5.809***
Rheinmetall	2.192**	1.757*	1.698*	1.672*	1.681*
Rockwell Collins	0.91	2.598**	2.95***	3.389***	3.592***
Rolls-Royce holding	1.34	2.377**	3.081***	3.741***	3.796***
Textron	2.075**	3.018***	3.597***	3.623***	3.849***
Ultra Electronics	-0.808	-2.689**	-2.641**	-5.063***	-3.569***
United Technologies	3.488***	4.475***	5.417***	5.898***	5.988***

Note: m stands for the number of (embedded) dimension which embed the time series into m-dimensional vectors, by taking each m successive points in the series. Value in cell represents BDS *z*-statistic; *, **, and * indicates rejection of *i.i.d.* residuals at 10, 5 and 1 percent level of significance respectively.**

Table 4b: BDS Test of nonlinearity on residuals for the stock returns equation in a VAR (1) model of stock returns and the geopolitical risk index

Company	Dimension				
	2	3	4	5	6
Badcock International	2.621**	3.781***	4.884***	5.567***	6.321***
BAE Systems	1.757*	3.012***	3.547***	4.21***	4.829***
Boeing	1.553	1.782*	3.036***	3.884***	4.711***
Booz Allen Hamilton	0.503	-6.054***	-3.229***	-2.031**	-1.207
Cobham	2.529**	2.827**	2.158**	1.749*	2.306**
Elbit Systems	4.915***	-9.415***	-7.763***	-4.704***	-3.097***
Esterline Technologies	1.709*	2.078**	2.512**	2.666**	2.811**
General Dynamics	5.694***	6.655***	7.383***	7.468***	7.726***
Harris Corporation	2.255***	2.923***	3.44***	3.729***	3.601***
Huntington Ingalls	3.218*	3.642**	4.095**	4.68**	4.846***
L3 Communications	1.75*	2.233**	2.284**	2.75**	2.961***

Leidos Holdings Inc.	1.9*	2.055**	1.89*	0.82	0.331
Lockheed Martin	4.358***	5.174***	6.397***	7.399***	8.19***
Mantech International	1.658*	1.552	2.194**	2.675**	2.955***
Northrop Grumman	5.94***	6.167***	7.338***	8.465***	9.339***
Orbital ATK	0.785	1.917*	2.264**	2.724**	2.877***
OSI Systems	5.082***	5.847***	6.443***	7.244***	7.789***
Raytheon	3.807***	5.175***	5.669***	5.567***	5.798***
Rheinmetall	2.201	1.773**	1.717**	1.7**	1.711***
Rockwell Collins	0.723	2.652**	2.992**	3.446**	3.786***
Rolls-Royce holding	1.615	2.586**	3.326***	3.849***	3.851***
Textron	2.255**	3.157***	3.73***	3.797***	4.037***
Ultra Electronics	-0.492	-2.564**	-2.539**	-4.982***	-3.519***
United Technologies	3.351***	4.228***	5.155***	5.586***	5.679***

Note: See Notes to Table 4a.

Table 5: *k*-th Order Test of Causality (Nishiyama *et al.,* 2011)

Company	Returns	Squared returns	Realized volatility
Badcock International	2.99	8.44	11.26
BAE Systems	8.10	4.16	26.26*
Boeing	0.69	7.12	24.73*
Booz Allen Hamilton	3.62	3.33	6.49
Cobham	0.23	5.95	91.45*
Elbit Systems	1.17	7.99	42.50*
Esterline Technologies	2.55	13.15	8.05
General Dynamics	2.91	15.04*	21.94*
Harris Corporation	1.60	6.14	23.76*
Huntington Ingalls	2.75	5.41	9.66
L3 Communications	0.26	9.22	31.92*
Leidos Holdings Inc.	5.65	1.79	11.19
Lockheed Martin	2.99	10.05	28.70*
Mantech Internaional	3.38	8.22	10.95
Northrop Grumman	6.78	18.27*	37.86*
Orbital ATK	3.37	7.39	2.29
OSI Systems	3.42	12.46	6.02
Raytheon	1.70	5.75	13.79
Rheinmetall	1.41	7.13	22.07*
Rockwell Collins	4.13	6.35	8.43
Rolls-Royce holding	4.22	5.42	20.58*
Textron	11.51	8.88	9.45
Ultra Electronics	4.47	4.39	3.12
United Technologies	0.97	10.08	22.14*

Note: * indicates rejection of the null of non-causality for returns, squared returns and realized volatility due to the geopolitical risk index at 5 percent (critical value: 14.38) level of significance.

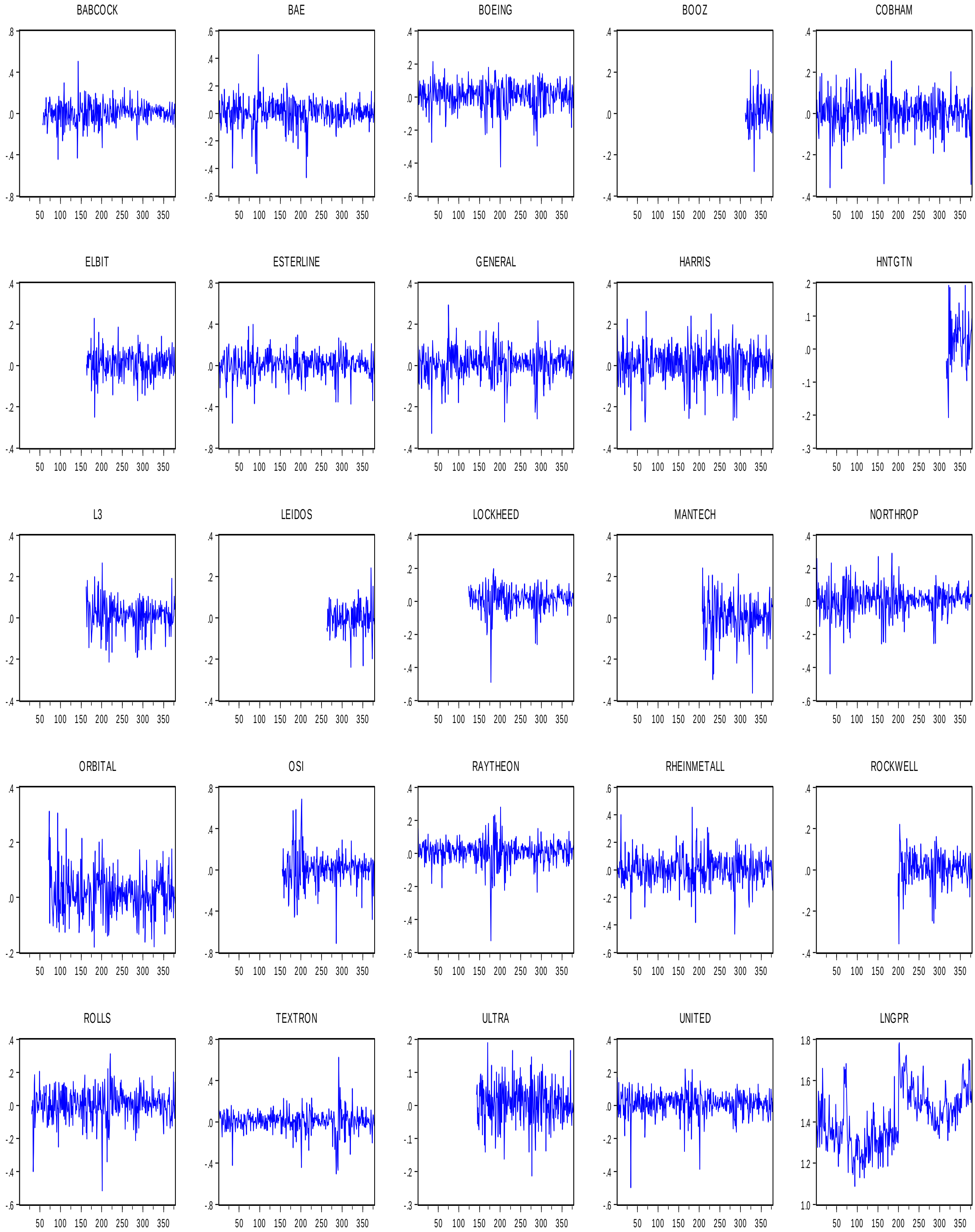

Figure 1: Plot of stock returns and natural log of the GPR index