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ORIGINAL PAPER

Did Baltic stock markets offer diversification benefits during the recent financial turmoil? Novel evidence from a nonparametric causality-in-quantiles test

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Abstract Motivated by financial liberalization investors seek for new investment opportunities through international portfolio diversification. To this end we explore any asymmetric causal relationship between developed European stock markets (Germany, France and UK) and emerging Baltic markets namely; Estonia, Latvia and Lithuania. Our analysis focuses on the period before and after countries' EU accession and pre- and post the global financial crisis. For this purpose, both the standard parametric test for causality and a novel nonparametric test for causality-in-quantiles are employed. The results of both the parametric and nonparametric Granger causality test support a causal relationship in mean that runs from all of the major markets to the Baltic markets across both samples. The results imply the existence of significant nonlinear return and volatility spillover from European markets to Baltic markets. Policy implications for international investors are also discussed.

Keywords Baltic stock markets · Non parametric · Quantile causality · Diversification benefits · Global financial crisis

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1 Introduction

Liberalization of capital markets has offered new opportunities for international diversification to investors. A successful diversification strategy across international stock markets implies that these markets are not heavily interrelated (Grubel 1968; Lessard 1973; Solnik 1974; Longin and Solnik 1995). Identifying the channels through which shocks are spreading from one market to another has direct impact to passive and active international investment strategies, portfolio diversification, and rebalancing. Moreover, the cross-market linkages and the potential gains from global investing have caught the attention of researchers and policy makers especially during turbulent periods.

Prior research on the integration of international stock markets maps its way in two distinct strands. A rather prolific strand of literature has provided empirical evidence of a negative correlation between stock returns in emerging stock markets and developed stock markets implying diversification benefits for international investors. The early contributions in the literature explaining the gains from international portfolio diversification were put forward by Eun and Resnick (1984), Errunza and Padmanabhan (1988), Meric and Meric (1989) and Korajczyk (1996). The most relevant and recent work in this field also includes Darrat et al. (2000), Gilmore and McManus (2002), Lamba (2005), Arouri and Jawadi (2009), Maneschiöld (2006), Stasiukonytė and Vasiliauskaitė (2008) and Nikkinen et al. (2012).

The level of integration between emerging markets of Latin America and Asia and mature stock markets of Western Europe and the United states has monopolized international stock market studies such as Kasa (1992), Richards (1995), Korajczyk (1996), Lamba (2005), Arshanapalli and Doukas (1996), and Arouri and Jawadi (2009).

Currently, there is growing literature on integration of emerging Central European markets with the leading developed stock markets of Europe and the United States based on studies by Jochum et al. (1999), MacDonald (2001), Gilmore and McManus (2002), and Voronkovat (2004). These studies show that the emerging Central European stock markets are becoming more integrated with the developed stock markets. Another strand of literature examines the relationship between South Eastern European stock markets and leading mature markets of USA and Europe (Syriopoulos and Roumpis 2009; Guidi and Ugur 2014) and reports some diversification benefits.

The other strand of literature focuses on financial integration between major international stock markets. These studies include data from Japan, US and some leading European markets (see inter alia Bekaert and Harvey 1995; Hardouvelis et al. 2006). Research in this field is largely motivated by the pivotal role of these stock markets in the international financial system and they focus on return and volatility spillovers.

However literature on Baltic stock markets and their level of integration with mature markets is relatively scarce. This justifies our choice of the Baltic States over other emerging markets. The most relevant and recent work in this area includes, Maneschiöld (2006), Stasiukonytė and Vasiliauskaitė (2008), and Nikkinen et al. (2012).

Arouri and Jawadi (2009) explore the stock market integration dynamics of two emerging countries namely; the Philippines and Mexico into the international capital market using a nonlinear cointegration method focusing on the period 1988–2008. Their paper shows evidence of varying degrees of nonlinear integration of these two emerging stock markets into the world capital market. Korajczyk (1996) applies the asset-pricing model to measure the degree of stock market integration in four developed markets and twenty emerging markets. In his paper he claims that emerging stock markets are more segmented than developed markets.

Darrat et al. (2000) finds that the emerging stock markets in the Middle East, (Cairo, Casablanca and Amman) are highly integrated within themselves but segmented from the global markets. Similarly, Lamba (2005) paper applies the same modelling techniques. However Lamba (2005) focuses on the South Asian capital markets of India, Pakistan and Sri Lanka. The results show that the Indian stock market is highly integrated into the major developed markets whereas Pakistan and Sri Lanka are segmented from the major markets. The paper also finds that the emerging markets are increasingly becoming integrated among themselves. Most recently, Al Nasser and Hajilee (2016) report evidence of the existence of short-run integration among stock markets in emerging countries (Brazil, China, Mexico, Russia and Turkey) and the developed markets (USA, UK and Germany).

Gilmore and McManus (2002) explore short and long term dynamics between the US stock market and emerging markets of Central Europe (the Czech Republic Hungary, Poland). Their results show that there exist minimal short term correlations between the European stock markets and the US stock market. Based on their main findings, they suggest that investors in the US can lower their risk by investing in the emerging markets of Central Europe which offer international portfolio diversification opportunities. Contrary, Voronkovat (2004) finds evidence of increasing level of integration between Central European markets and developed European markets. In a related study, Reboredo et al. (2015) examine the dependence structure between four Central and Eastern European (CEE) stock markets (Czech Republic, Hungary, Poland and Romania) using static and dynamic copula functions and document positive dependence between all CEE stock markets.

Maneschiöld (2006) examines the short-and long-run dynamics between the Baltic and international capital markets (United States, Japan, Germany, the United Kingdom, and France). The paper applies the Johansen cointegration method and show that the Baltic capital markets are not strongly integrated with international markets, thus indicating a good area of investment for international investors seeking to diversify their portfolio (Table 1).

With the above in mind our goal is to investigate the linkages between stock returns in mature and leading markets and the Baltic stock markets. In particular, this paper explores any causal relationship between stock market returns in developed European markets and emerging Baltic markets namely; Estonia, Latvia and Lithuania. To this end we set off to employ for the first time under this framework the nonparametric test for causality-in-quantiles approach. Thus, the aim

Table 1 Financial indicators of the Baltic countries. *Source* World Bank

Variables	Mean (1995–2012)	SD (1995–2012)
Estonia		
Market capitalisation of listed companies, USD, Billions[a]	2,841,496,277	1,789,988,815
Listed domestic companies, Units	18	5
Turnover ratio[b], %	26	26
Portfolio[c]—net inflows, current USD[d]	−28,288,982	369,224,003
Latvia		
Market capitalisation of listed companies, USD, Billions	1,181,142,493	905,648,516
Listed domestic companies	45	16
Turnover ratio, %	13	13
Portfolio—net inflows, current U	8,021,278	21,558,466
Lithuania		
Market capitalisation of listed companies, USD, Billions	3,860,776,732	3,153,798,169
Listed domestic companies	117	170
Turnover ratio, %	12	6
Portfolio—net inflows, current U	12,554,087	63,023,488

[a] The data for Estonia starts in 1997

[b] Turnover ratio is the total value of shares traded during the period divided by the average market capitalization for the period. Average market capitalization is calculated as the average of the end-of-period values for the current period and the previous period. The data starts in 1996 for Latvia and Lithuania and 1998 for Estonia

[c] Portfolio equity includes net inflows from equity securities other than those recorded as direct investment and including shares, stocks, depository receipts (American or global), and direct purchases of shares in local stock markets by foreign investors

[d] The data starts in 1996

of this study is to enhance our understanding of the dynamic relationship that exists between stock returns in emerging markets and developed markets in various points of the returns distribution. Our rationale for examining the Baltic countries lies in the fact that research regarding integration of these markets is scarce (Jeong et al. 2012; Stasiukonyte and Vasiliauskaite 2008; Nikkinen et al. 2012). Moreover, these three frontier markets have registered a remarkable GDP growth rate among all EU members in the period before global financial crisis 2004–2007. This rapid economic growth was mainly fuelled by FDI inflows and was abruptly terminated by the outburst of the financial crisis of 2008/09 (Nikkinen et al. 2012). As it is reported in Table 2 during the period 2001–2005 Baltic stock markets registered remarkably high returns at an annual basis compared to mature European stock markets. For example, in 2005 the stock market in Latvia experienced an annual return of 63.54 % while during the same period DAX 30 achieved a 27.07 % annual return.This behaviour of the Baltic stock markets could lead us to consider them as segmented markets from the mature European core countries.

Our paper will mainly build on the work by Nikkinen et al. (2012) and Stasiukonytė and Vasiliauskaitė (2008). Stasiukonyte and Vasiliauskaite (2008) acknowledges that there is still scarce research carried out regarding integration

Table 2 Annual stock market returns of Baltic and selected mature markets. *Source* Datastream, Authors' estimations

Year	Latvia (%)	Estonia (%)	Lithuania (%)	DAX 30 (%)	CAC 40 (%)	FTSE 100 (%)
2001	46.89	17.21	−18.49	−19.79	−20.33	−14.09
2002	−14.30	12.08	12.20	−43.94	−31.92	−22.17
2003	47.02	58.66	105.80	37.08	19.87	17.89
2004	43.45	40.16	68.18	7.34	11.40	11.25
2005	63.54	43.59	52.93	27.07	26.60	20.78
2006	−3.08	10.66	9.78	21.98	20.87	14.43
2007	−9.19	2.38	4.38	22.29	4.16	7.36
2008	−54.43	−66.69	−65.14	−40.37	−40.33	−28.33
2009	2.82	37.83	46.04	23.85	27.58	27.33
2010	41.08	69.83	56.49	16.06	0.55	12.62
2011	−5.68	−19.11	−27.06	−14.69	−13.39	−2.18
2012	6.67	26.63	18.84	29.06	20.37	9.97
2013	16.22	12.16	18.73	25.48	22.22	18.66

within and between the Baltic countries and European markets. To study these relationships, they make use of recent quantitative research methods such as unit root, Engle-Granger, Granger causality test and vector autoregressive analysis (VAR). However their paper finds contradicting and mixed results mainly due to the different methods employed.

Nikkinen et al. (2012) examine stock market integration between advanced European stock markets and emerging Baltic stock markets focusing on the 2008–2009 financial crisis. They particularly study the degree to which emerging stock markets are integrated into European stock markets during a crisis period. Using the Granger (1969) causality test, quantile regressions and VAR, their study shows that the Baltic markets are segmented from the developed European stock markets before the crisis while increasingly become integrated during crisis periods.

Our study contributes to the literature that studies the asymmetric nature of cross market linkages during volatile periods or downward markets (see inter alia Longin and Solnik 2001; Ang and Chen 2002; Kearney and Poti 2006). Our paper differs from Nikkinen et al. (2012) in various aspects. Their paper employs quantile regressions which is not robust against the nonlinearities and outliers.

The non-parametric Granger causality-in-quantile test has the advantage of robustness properties of the conditional quantile in that it allows us to observe the causal effects over the entire distribution of the data rather that at one fixed point in time (Campbell and Cochrane 1999). Second we examine whether EU accession alone has an effect of Baltic markets' integration with the developed markets.

It is well known that most financial time series data display nonlinear dynamics and have nonelliptic distribution. In view of these properties, this study employs a modified version of causality-in-quantile test of Jeong et al. (2012) along the lines of nonparametric Granger causality test of Nishiyama et al. (2011). Thus, the nonparametric causality-in-quantile test employed in our study has following novelties. First, the tests are robust to functional misspecification errors and can detect general dependence between time series. This is particularly important in our application, since it is well known that stock market data display nonlinear dynamics. Second, the test statistic does not only test for causality on the mean, it also tests for causality that may exist in the tail area of the joint distribution of the series. As stock market data display nonelliptic distribution, the tests we employ are well suited for causality analysis between the financial time series data. Third, the tests easily lend themselves to test for causality in variance. The causality in variance test is also implemented as nonparametric causality in variance tests. Testing for causality in variance is crucial for financial time series due to well-known volatility spillover phenomenon, where causality in conditional mean (first moment) may not exist, but there may be second or higher order causality.

Previewing our results we document a causal relationship between the Baltic countries and all the major markets as revealed by the nonparametric quantile causality test. There is causality that runs from all major markets to the Baltic stock markets across various points of returns distribution, with the effect being more intense during financial turmoil. Most interestingly our findings imply the existence of significant nonlinear return and volatility spillover from European markets to Baltic markets. Our results also indicate that both the recent global financial crisis and the accession of the Baltic markets to the EU intensified and in some cases created causal effects to the major markets, therefore reducing investment portfolio diversification opportunities. Consistent with Nikkinen et al. (2012) and Jeong et al. (2012) our paper highlights the caveats of the normal Granger causality test.

The rest of the paper unfolds as follows. We provide a brief background on the Baltic countries in Sect. 2, while Sect. 3 presents the methodology. Section 4 outlines the data. Section 5 presents the empirical results, and Sect. 5 concludes.

2 Methodology

2.1 Linear granger causality test

We use the Granger (1969) causality test to test for linear causality between the returns of the aggregate Baltic markets (*bmr*) and the major markets (*mmr*). The test was conducted on a bivariate autoregression model:

$$\Delta bmr = \alpha_0 + \sum_{p=1}^{n} \alpha_p \Delta bmr_{t-p} + \sum_{p=1}^{n} \beta_p \Delta mmr_{t-p} + \varepsilon_{bmr,t} \tag{1}$$

$$\Delta mmr = \zeta_0 + \sum_{p=1}^{n} \zeta_p \Delta bmr_{t-p} + \sum_{p=1}^{n} \psi_p \Delta mmr_{t-p} + \varepsilon_{mmr,t}, \tag{2}$$

where Δ is the first difference operator, α_0 and ζ_0 are constants, α_p, ζ_p, β_p and ψ_p are parameters, and $\varepsilon_{bmr,t}$ and $\varepsilon_{mmr,t}$ are error terms. The null hypothesis is that the major European stock markets do no Granger cause Baltic stock markets in Eq. 1. The reported F-statistics are for the joint hypothesis that β_p equal to zero for Eq. 1. If the null is rejected, then there exists a causality from the major European stock markets to the Baltic markets.

2.2 Nonparametric granger causality test in quantiles

Granger (1969) developed the earliest key method for exploring linear causal relationships between stock returns in different financial markets. However, linear causality tests are not suitable for determining causality in nonlinear financial variables because they fail to detect non-linear causality relationships. To address the above issues Nishiyama et al. (2011) developed nonparametric Granger causality tests based on the kernel density estimation. Further, Jeong et al. (2012) addressed the gaps that existed in literature between causality in the conditional mean and nonlinear relationships by designing a nonparametric test of Granger causality-in-quantile based on the kernel density method.

The Granger causality-in-quantile method gained its popularity in financial economics following the benefits from international portfolio diversification and the ability to manage risk. This method has the desirable property of robustness properties of the conditional quantile in that it allows us to observe the causal effects over the entire distribution of the data rather that at one fixed point in time (Campbell and Cochrane 1999; Hong et al. 2009).

This method deals with time series data of two variables and establishes the direction of causality between two economic variables. Majority of papers use Granger causality in the conditional mean to establish their results. However, the conditional mean is not a reliable measure to determine causality especially between financial returns if the distribution of the variables is ambiguous or is fat tailed. The conditional mean is an overall summary of the conditional distribution which does not capture causal dynamics in the entire distribution but around particular regions of the conditional distribution (Jeong et al. 2012). This is supported by Lee and Yang (2007) who show that that causality between money and income only exists in the tail quantiles but not in the centre of the distribution. Another advantage of using Granger causality-in-quantile to establish causality between financial returns is that correlations between stock returns highly depend on existing market arrangements or regimes (Ang and Bekaert 2002; Longin and Solnik 2001; Ang and Chen 2002). Financial downturns or economic crises are highly characterized by strong correlations between financial returns.

The following section outlines the Granger (1988) causality-in-quantile method: For simplicity, we assume that the stock returns $\{y_t,\ x_t\}$ are observable,

1. x_t does not cause y_t in the θ-quantile with respect to $\{y_{t-1},\ldots,y_{t-p},x_{t-1},\ldots,x_{t-p}\}$ if

$$Q_\theta\{y_t|y_{t-1},\ldots,y_{t-p},x_{t-1},\ldots,x_{t-p}\} = Q_\theta\{y_t|y_{t-1},\ldots,y_{t-p}\} \tag{3}$$

2. x_t is a prima facie cause y_t in the θ-quantile with respect to $\{y_{t-1},\ldots,y_{t-p},x_{t-1},\ldots,x_{t-p}\}$ if

$$Q_\theta\{y_t|y_{t-1},\ldots,y_{t-p},x_{t-1},\ldots,x_{t-p}\}\neq Q_\theta\{y_t|y_{t-1},\ldots,y_{t-p}\} \tag{4}$$

where $Q_\theta\{y_t|\cdot\}$ is the θ-th conditional quantile of y_t given, which depends on t and $0<\theta<1$. Define $Y_t\equiv(y_{t-1},\ldots,y_{t-p})$, $X_{t-1}\equiv(x_{t-1},\ldots,x_{t-p})$, $Z_t=(X_t,Y_t)$, and $F_{y_t|Z_{t-1}}(y_t,Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t,Y_{t-1})$ are the conditional distribution function of y_t given Z_{t-1} and Y_{t-1}, respectively.

The conditional distribution $F_{y_t|Z_{t-1}}(y_t,Z_{t-1})$ is assumed to be absolutely continuous in y_t for almost all Z_{t-1}. If we denote $Q_\theta(Z_{t-1})\equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1})\equiv Q_\theta(y_t|Y_{t-1})$, we have, $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\}=\theta$ with probabilty 1.

Consequently, the hypothesis to be tested based on definitions (1) and (2) are

$$H_0:\quad P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\}=\theta\right\}=1\text{ a.s.} \tag{5}$$

$$H_1:\quad P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\}=\theta\right\}<1\text{ a.s.} \tag{6}$$

Zheng (1998) mitigates the problem of testing quantile restriction to testing specific type of mean restriction. Jeong et al. (2012) employs as a distance the measure $J=\{\varepsilon_t E(\varepsilon_t|Z_{t-1})f_z(Z_{t-1})\}$ where ε_t is the regression error term and $f_Z(Z_{t-1})$ is the marginal density function of Z_{t-1}. The regression error ε_t arises from the fact that the null hypothesis in (3) can only be true if and only if $E[\mathbf{1}\{y_t\leq Q_\theta(Y_{t-1})|Z_{t-1}\}]=\theta$ or equivalently $\mathbf{1}\{y_t\leq Q_\theta(Y_{t-1})\}=\theta+\varepsilon_t$, where $\mathbf{1}\{\cdot\}$ is the indicator function. Jeong et al. (2012) specify the distance function as

$$J=E\left[\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\}-\theta\right\}^2 f_Z(Z_{t-1})\right] \tag{7}$$

In Eq. (7), it is important to note that $J\geq 0$ and $J=0$ holds if and only if the null hypothesis H_0 in Eq. (5) is true, while $J>0$ holds under the alternative H_1 in Eq. (6). Jeong et al. (2012) shows that the feasible kernel-based test statistic based on J has the following form:

$$\hat{J}_T=\frac{1}{T(T-1)h^{2p}}\sum_{t=p+1}^{T}\sum_{s=p+1,s\neq t}^{T}K\left(\frac{Z_{t-1}-Z_{s-1}}{h}\right)\hat{\varepsilon}_t\hat{\varepsilon}_s \tag{8}$$

where $K(\cdot)$ is the kernel function with bandwidth h and $\hat{\varepsilon}_t$ is the estimate of the unknown regression error, which is estimated from

$$\hat{\varepsilon}_t=\mathbf{1}\{y_t\leq Q_\theta(Y_{t-1})\}-\theta \tag{9}$$

where $\hat{Q}_\theta(Y_{t-1})$ is an estimate of the θth conditional quantile of y_t given Y_{t-1}. We estimate $\hat{Q}_\theta(Y_{t-1})$ using the nonparametric kernel method as

$$\hat{Q}_\theta(Y_{t-1})=\hat{F}^{-1}_{y_t|Y_{t-1}}(\theta|Y_{t-1}) \tag{10}$$

Here, $\hat{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1})$ is the Nadarya-Watson kernel estimator is given by

$$\hat{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1}) = \frac{\sum_{s=p+1,s\neq t}^{T} L((Y_{t-1} - Y_{s-1})/h)1(y_s \leq y_t)}{\sum_{s=p+1,s\neq t}^{T} L((Y_{t-1} - Y_{s-1})/h)} \tag{11}$$

with the kernel function $L(\cdot)$ and bandwidth h.

We also test for volatility spillover in stock returns using Granger causality in the second moment. In general, causality in the m-th moment implies causality in the k-th moment for $m < k$. This is need to be considered for specifying causality in higher order moments restrictions.

To test for nonparametric Granger quantile causality in variance we employ the general nonparametric Granger quantile causality test by Nishiyama et al. (2011). Assuming strong moment conditions, density weighted nonparametric tests in higher moments possess the same asymptotic normal distribution as the test for causality in first moment. Equation (12) is an illustration of the causality in higher order moments given as

$$y_t = g(Y_{t-1}) + \sigma(X_{t-1})\varepsilon_t \tag{12}$$

where ε_t is a white noise process, $g(\cdot)$ and $\sigma(\cdot)$ are unknown functions that satisfy certain conditions for stationarity. The specification in Eq. (12), does not allow Granger causality from x_t to y_t, but certainly allows predictive power (in the Granger causality sense) from x_t to y_t^2 with $\sigma(\cdot)$ being general nonlinear function. The Granger causality in variance definition does not require an explicit specification of squares of X_{t-1}. A model like Eq. (12) has a null and alternative hypothesis for causality in variance given by

$$H_0: \quad P\left\{F_{y_t^2|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1 \text{ a.s.} \tag{13}$$

$$H_1: \quad P\left\{F_{y_t^2|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1 \text{ a.s.} \tag{14}$$

To obtain the feasible test statistic for testing the null hypothesis H_0 in Eq. (12) we replace y_t in Eqs. (8)–(11) with y_t^2. To overcome the problem that causality in the conditional first moment (mean) implies causality in the second moment (variance), we interpret quantile causality in higher order moments using the following model:

$$y_t = g(X_{t-1}, Y_{t-1}) + \varepsilon_t \tag{15}$$

Higher order quantile causality for this model can be specified as

$$H_0: \quad P\left\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1 \quad \text{a.s.} \quad \text{for} \quad k = 1, 2, \ldots, K \tag{16}$$

$$H_1: \quad P\left\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1 \quad \text{a.s.} \quad \text{for} \quad k = 1, 2, \ldots, K \tag{17}$$

Following this definition, x_t Granger causes y_t in quantile θ up to K-th moment. The null specified in Eq. (16) is used to construct the test statistic in Eq. (8) for each k. It is not easy to combine the different statistics for each $k = 1, 2, \ldots, K$ into one statistic for the joint null in Eq. (13) because the statistics are mutually correlated (Nishiyama et al. 2011). To address this problem, we follow the sequential testing approach in Nishiyama et al. (2011). This approach first tests for nonparametric Granger causality in the first moment $(k = 1)$. Rejecting the null hypothesis of non-causality means that we can stop and interpret this result as a strong indication of possible Granger quantile causality in variance. However, failure to reject the null for $k = 1$, does not automatically translate to no causality in the second moment and, thus, we can still construct the tests for $k = 2$. This approach allows us to test the existence of causality not only in variance as well as the causality in the mean and variance successively.

Empirical implementation of the feasible causality-in-quantile tests entails specifying three important choices: the bandwidth h, the lag order p, and the kernel type for the kernels $K(\cdot)$ and $L(\cdot)$ in Eqs. (8) and (11), respectively. The lag order p is determined using the Schwarz Information Criterion (SIC) in a linear bivariate vector autoregressive (VAR) model, which is 1 for all cases.[1] The bandwidth h is selected using the least squares cross-validation method of Rudemo (1982) and Bowman (1984). We employ the Gaussian kernel type to specify kernel types for kernels $K(\cdot)$ and $L(\cdot)$.

3 Data

The data used in the analysis consists of daily closing prices of stock indices that span the period from 16 February 2001 to 16 July 2014. Total return stock indices were sourced from Thomson Datastream. Indices from the major economies include the DAX 30 Performance Index for Germany, CAC 40 for France, FTSE 100 for United Kingdom and both the Euro Stoxx and Euro Stoxx 50 indices for Europe as a whole. The Baltic index is used as a proxy for the aggregate stock index of the three countries. Returns of the selected indices were computed by taking the difference of the logarithmic values. In the context of our analysis, we split our sample into four different sub samples in order to examine the effect of crisis and EU accession on stock market linkages. It should be noted that Baltic countries became member of the European Union in May 2004. For this purpose our analysis is separately conducted in the following subsamples: start of the sample till April 2004 (pre-EU accession) and May 2004 till the end of the sample (post-EU accession) and start of the sample till November 2007 (pre-crisis period) and December 2007 till the end of the sample (post-crisis period).

The Baltic stock markets resumed operation in the 1990s after being closed "at the beginning of the second World War", (Nikkinen et al. 2012). The first to open

[1] The SIC criterion is known to select a parsimonious number of lags and, thereby, prevents overparameterization problems associated with nonparametric approaches. In this case, however, the sequential modified Likelihood Ratio test, Final Prediction Error (FPE), Akaike Information Criterion (AIC) and the Hannan-Quinn Information Criterion (HQC) all chose a lag-length of one as well.

was the Vilnius stock exchange in Lithuania in 1993, followed by the Riga stock exchange in Latvia in 1995, and lastly Estonia's Tallinn stock exchange in 1996. Table 1 shows the basic statistics of the financial market conditions for the Baltic countries between 1995 and 2013. The Vilnius stock exchange is the biggest according to the mean of the market capitalisation, followed by the Tallinn stock exchange. However, between 1999 and 2004, market capitalisation for the Tallinn stock exchange exceeded that of the Vilnius stock exchange. The Riga stock exchange is the smallest. Even though the Tallinn stock exchange is the most active, there are more capital outflows by foreign investors compared to net inflows into Latvia and Lithuania. Estonia experienced increased capital outflows during the 2008—2012 period, with inflows recorded only in 2009.

We start our analysis with a simple unit root test in order to determine the order of integration of the variables. Given that the aim of the paper is to make use of a nonparametric approach, we use the Phillips and Perron (1988) unit root test. Unit root results[2] indicate that all the variables are stationary in their first difference (returns).

Table 3 shows both the descriptive statistics and the correlation of the stock returns as expressed in logarithmic form. The descriptive data analysis of the pre- and post-crisis period indicates that the global financial crisis increased both the volatility of the returns for the Baltic stock markets (as measured by the standard deviations) and the skewness of the distribution from extreme gains to extreme losses. Finally, there is also an upward shift in correlations between the Baltic markets and the major markets during/after the crisis.[3]

4 Parametric versus non-parametric Granger causality

Table 4 reports the results for the parametric Granger-causality test for the two samples adjusted for the date that Baltic countries became member of European Union. The results indicate that all the major markets have a causal effect on the aggregate Baltic markets, both before and after the EU accession and the global financial crisis.[4]

Granger non-causality tests assume that parameters of the VAR model used in testing are constant over time. This assumption is often violated because of structural changes and as Granger (1996) pointed out, parameter non-constancy is one of the most challenging issues confronting empirical studies today. Although the presence of structural changes can be detected beforehand and the estimations can be modified to address this issue using several approaches, such as including dummy variables and sample splitting, such an approach introduces pre-test bias.

[2] Which are available from the authors upon request.

[3] The data description is sensitive to the sub-samples selection. There is an increase in correlation during the global financial crisis period (12/2007—06/2009) and then a reduction post the global financial crisis (07/2009—07/2014). The mean for the global crisis period are all negative and then increases post the crisis.

[4] The results are not sensitive when the data is sub-sampled into the pre (02/2001–11/2007), during (12/2007–06/2009) and post (07/2009–07/2014) crisis. We still find that the Baltic markets have no causal effect on the major markets except on the UK market during the crisis period.

Table 3 Descriptive statistics and correlation matrix. *Source* Thomson Datastream

Descriptive statistics	Pre-crisis					Post-crisis				
	Baltic	Germany	Europe	France	UK	Baltic	Germany	Europe	France	UK
Mean	0.08	0.01	0.01	0.01	0.01	0.00	0.01	0.00	0.00	0.02
Median	0.08	0.06	0.02	0.02	0.02	0.00	0.04	0.00	0.01	0.01
Maximum	11.78	7.55	7.08	7.00	5.90	8.96	10.80	10.44	10.59	9.38
Minimum	−7.30	−8.87	−6.62	−7.68	−5.89	−8.82	−7.43	−8.19	−9.47	−9.27
SD	0.82	1.56	1.43	1.38	1.11	1.17	1.55	1.63	1.62	1.35
Skewness	0.34	−0.12	−0.05	−0.07	−0.25	−0.33	0.09	0.07	0.11	−0.10
Kurtosis	35.12	6.53	6.54	6.67	6.89	12.63	9.27	8.33	8.88	10.78
Jarque–Bera	76,143.92	921.82	923.41	996.60	1132.26	6714.59	2829.97	2045.02	2489.94	4358.02
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	149.84	17.73	15.03	19.15	26.23	−8.14	22.53	−1.83	0.85	30.13
Sum Sq. Dev.	1204.52	4284.08	3597.64	3360.28	2193.87	2363.54	4126.45	4571.39	4560.31	3132.95
Observations	1771	1771	1771	1771	1771	1728	1728	1728	1728	1728
Correlations										
Baltic	1					1				
Germany	0.10	1.00				0.35	1.00			
Europe	0.12	0.92	1.00			0.37	0.95	1.00		
France	0.12	0.87	0.97	1.00		0.38	0.93	0.98	1.00	
UK	0.12	0.78	0.88	0.88	1.00	0.37	0.87	0.90	0.92	1.00

Table 4 Parametric Granger Causality. *Source* Thomson Datastream

	F-stat	Probability	*F*-stat	Probability
	Pre-EU		Post-EU	
Europe to Baltic	23.96	0.00***	95.80	0.00***
Germany to Baltic	22.15	0.00***	86.71	0.00***
Baltic to Germany	0.13	0.72	2.44	0.12
France to Baltic	30.24	0.00***	119.23	0.00***
UK to Baltic	15.97	0.00***	101.62	0.00***
	Pre crisis		Post crisis	
Europe to Baltic	32.02	0.00***	77.20	0.00***
Germany to Baltic	37.48	0.00***	100.17	0.00***
France to Baltic	32.92	0.00***	66.98	0.00***
UK to Baltic	26.49	0.00***	81.05	0.00***

The lag order is determined using the SIC criterion

* Significant at 10 % level

** Significant at 5 % level

*** Significant at 1 % level

Moreover, the linear Granger causality tests do not have power against the existence of nonlinear relationships. Therefore, the results of linear Granger causality tests would not be reliable in the presence of structural breaks and nonlinearities.

In order to examine whether the relationship between the Baltic stock markets and major European markets has structural breaks and possibly nonlinearities we use rolling correlation estimates. Figure 1 reports rolling correlation estimates with a fixed rolling window size that is equal to 250 days. The rolling correlations estimates have similar pattern for Europe, Germany, France, and the UK. The most important feature of the rolling correlation estimates are their highly time varying feature. Indeed, the correlation of the Baltic markets were quite low before 2007 with negative correlations around 2005. The correlations increased form negative to positive 0.60 at the beginning of the global financial crises of 2007–2008. The correlation of the Baltic markets with the major European markets fluctuated between 0.20 and 0.60 in the 2008–2014 period.

The strong breaks in the correlation estimates given in Fig. 1 imply that the results of the linear Granger causality tests should be interpreted with caution and their robustness should be checked with methods that are robust to structural breaks and nonlinearities. Thus, we use the nonparametric causality-in-quantile test to check the robustness of the linear Granger causality tests.

Figures 2, 3, 4 and 5 report test statistics for the nonparametric test for causality-in-quantile for the pre-EU, post-EU, pre-crises, post-crises periods from European, Germany, France, and the UK stock markets to Baltic stock markets. The thin grey line in the figures represents the critical value of 1.96. Parts a and b of Figs. 2, 3, 4 and 5 reports the tests results for the pre and post-EU accession periods. The results show that the quantile causality in variance from the major financial markets to the Baltic markets before the EU accession is statistically significant across all quantiles. UK and the aggregate European markets have a causal effect (in the conditional mean) to the Baltic markets across the quantiles $0.3 < \theta < 0.7$. After the EU accession, there is causality in both the conditional mean and variance from the major markets to the Baltic markets across all quantiles. The causality in conditional mean is high in the lower quantiles, $\theta < 0.5$ quantiles, i.e. during economic downturns.

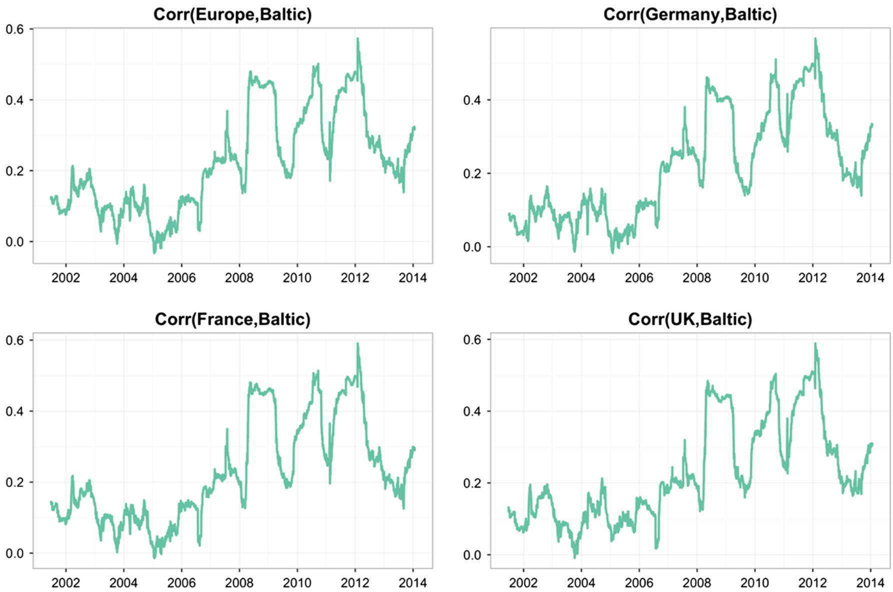

Fig. 1 Rolling correlation estimates

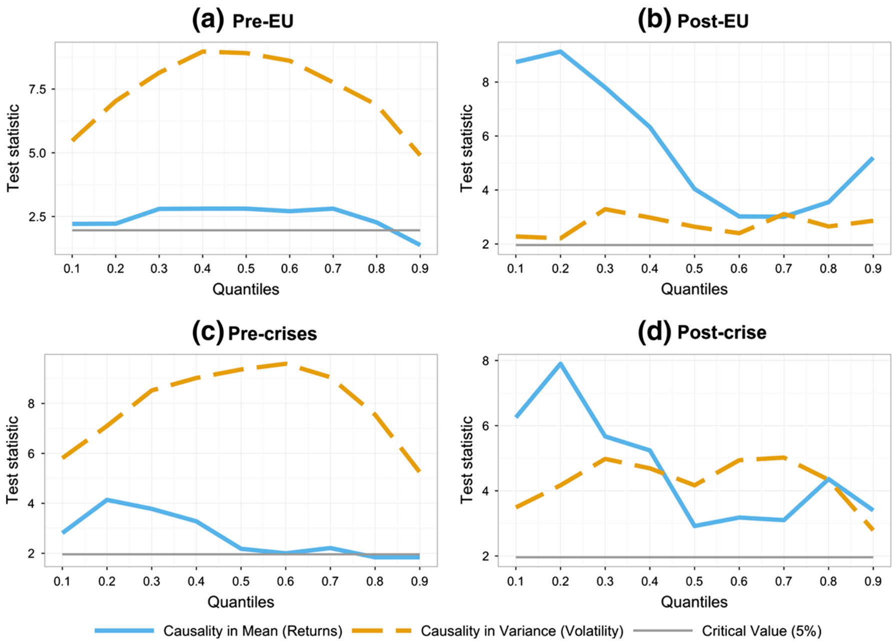

Fig. 2 Non-parametric quantile causality from Europe to Baltic

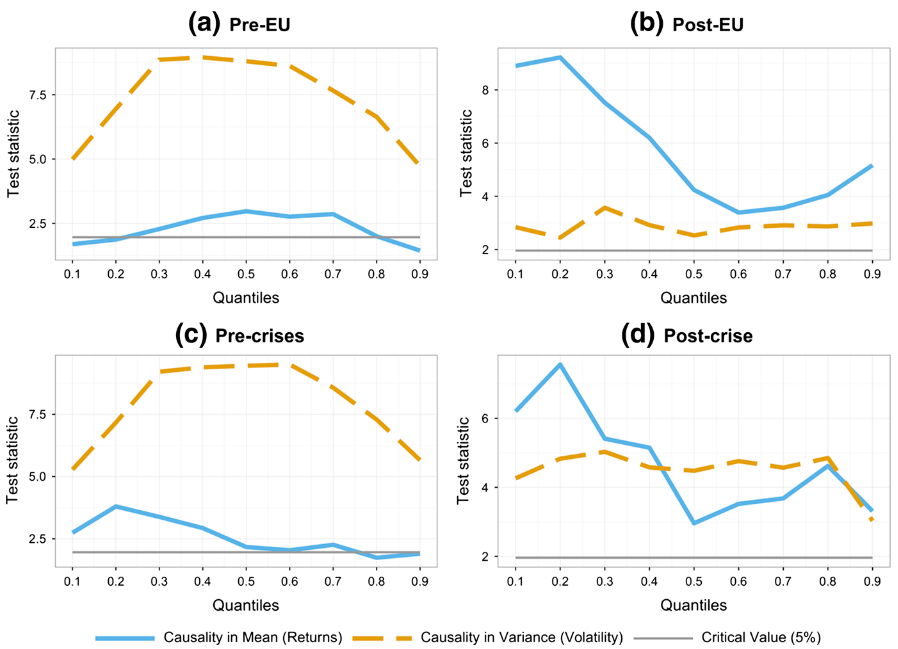

Fig. 3 Non-parametric quantile causality from Germany to Baltic

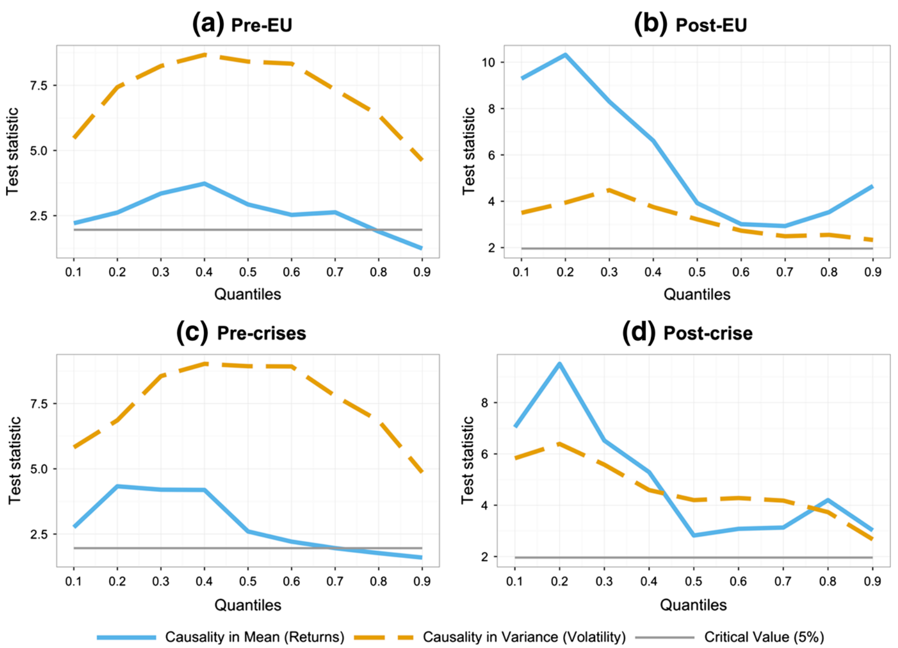

Fig. 4 Non-parametric quantile causality test from France to Baltic

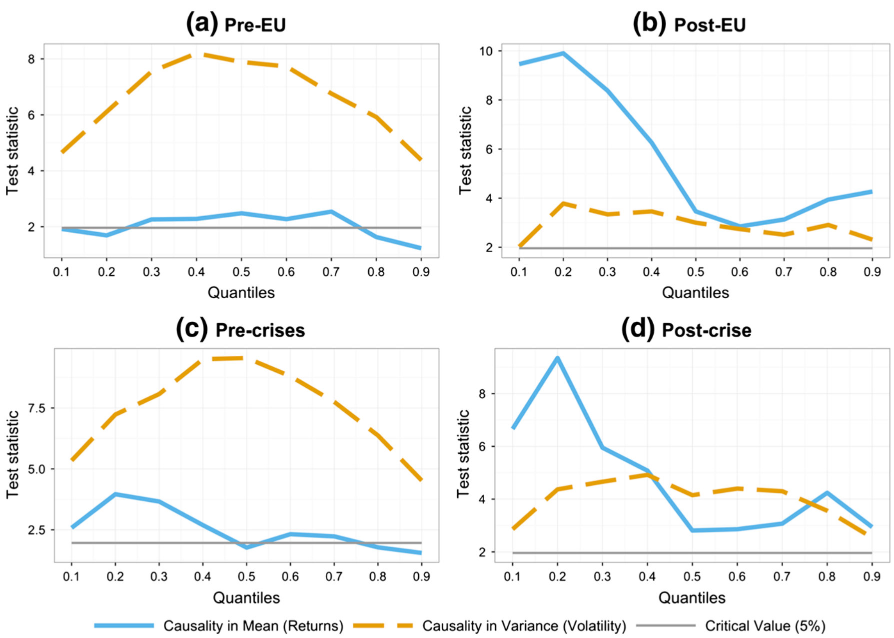

Fig. 5 Non-parametric quantile causality test from UK to Baltic

Parts c and d of Figs. 2, 3, 4 and 5 report the the nonparametric causality-in-quantile tests for the pre- and post-crisis. The global financial crisis period as defined by the National Bureau of Economic Research (NBER) is from December 2007 to June 2009. Given that the global financial crisis was shortly followed by the ongoing European sovereign debt crisis, we have divided the sample into two periods: January 2001 to November 2007 as the pre-crisis period; and December 2007 July 2014 as the post-crisis period.

Before the crisis, the causality in conditional variance from the major markets to the Baltic markets is significant across all quantiles whilst the causality in conditional mean is significant in the quantiles $0 \leq \theta < 0.7$.

In the post crisis period, the developed markets at all levels exhibit significant predictive power for the returns in the Baltic markets across all quantiles. The causal effect is stronger when $\theta < 0.5$ which coincides with the post-EU nonparametric results. This implies that the Baltic markets tend to respond more to the developed markets during financial turbulence. This comes as no surprise considering that emerging markets are more vulnerable to negative shocks from negative investment sentiment.

5 Conclusion

This paper's objective is to explore any asymmetric stock market integration between developed European markets of Germany, France and UK and emerging Baltic stock markets of Estonia, Latvia and Lithuania in the period 2001–2014. We examine integration both at a country level employing national stock market indices and at an aggregate level employing the Eurostoxx 50 index and the Baltic index. Our period of analysis is extensive and spans the global financial crisis and the ensuing Eurozone sovereign debt crisis. Our novelty compared to previous studies is the use for the first time in this framework of a nonparametric causality test across different quantiles. In particular this study employs a modified version of causality-in-quantile test of Jeong et al. (2012) along the lines of nonparametric Granger causality test of Nishiyama et al. (2011).

The results provided evidence in favour of the notion that movements in stock returns of the three major European markets (UK, France & Germany) have a significant effect on stock returns of the Baltic markets especially during financial turmoil. These results are consistent with the findings of other researchers such as Nikkinen et al. (2012) who showed that Baltic markets are more integrated with developed European stock markets during crisis periods. As for the effect of EU accession on the level of integration we document that all the mature markets have a causal effect on the aggregate Baltic markets, both before and after the EU accession. Employing the non parametric test we report a statistically significant causality in variance from the major financial markets to the Baltic markets before and after the EU accession across all quantiles. Interestingly, the causality in conditional mean is more intense in the lower quantiles of the returns distribution.

Our results entail significant implications for international investors seeking for diversification opportunities. Our findings reinforce previous evidence (Nikkinen et al. 2012) validating the hypothesis of stock market integration of the Baltic stock markets which is more pronounced during turbulent periods. However, we should point out that the results imply the existence of significant nonlinear return and volatility spillover from European markets to Baltic markets. Therefore, the existence of significant dependence of the Baltic markets to European markets is regime-dependent and may not be observed in all periods. Therefore, investors should be cautious in their investment decisions as the non-existence of significant dependence in certain periods will not hold in other periods where the market regime is different.

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