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# Stock market volatility and business cycle: Evidence from linear and nonlinear causality tests ☆

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ABSTRACT

This paper investigates the relationship between stock market volatility and the business cycle in four major economies, namely the US, Canada, Japan and the UK. We employ both linear and nonlinear bivariate causality tests and we further conduct a multivariate analysis to explore possible spillover effects across countries. Our results suggest that there is a bidirectional causal relationship between stock market volatility and the business cycle within each country and additionally reveal that the recent financial crisis plays an important role in this context. Finally, we identify a significant impact of the US on the remaining markets.



## 1. Introduction

The relationship between stock market volatility and the business cycle is the focal point of several studies in the extant literature while it is also an issue of vital importance for policy and investment decision makers (e.g., Fama, 1990; Schwert, 1989, 1990a, 1990b; Corradi et al., 2013; Chauvet et al., 2014). At the business cycle frequency, most related empirical work has focused on whether stock market volatility which exhibits a different behaviour over expansion and recession periods, can be predicted by various macroeconomic variables (see Schwert, 1989; Hamilton and Lin, 1996). Recent work also establishes a strong link between stock market volatility and macroeconomic fundamentals (see, Engle and Rangel, 2008; Engle et al., 2008; Diebold and Yilmaz, 2010; and Corradi et al., 2013). Nevertheless, this is still a topic which remains largely unstudied since the literature generally places more weight on measuring, modelling and forecasting volatility rather than exploring the links with its underlying determinants (Diebold and Yilmaz, 2010). On the other hand, there are even fewer studies that consider the opposite direction and employ stock market volatility to predict real economic activity (e.g., Andreou et al., 2000; Fornari and Mele, 2013). However, understanding the dynamics and behaviour of stock market volatility and examining its potential spillover effects on real economic activity and vice versa is a matter of utmost significance for two reasons. First, it can help market participants to improve their investment decisions and second, it can have important implications for the effectiveness of various economic policies.

In this context, some important empirical questions arise: Is there a causal relationship between stock market volatility and real economic activity which runs in either direction within an international setting? Furthermore, is the nature of this relationship linear as most studies assume or are there nonlinearities that need to be taken into consideration? Finally, are there any links between these variables across countries? This paper aims to provide empirical evidence on these unexplored avenues of research and contributes to the literature in the following ways.

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First, we empirically investigate the causal relationship between stock market volatility and the business cycle (represented by the industrial production growth rate) within an international setting using both linear and nonlinear bivariate tests. Specifically, we employ monthly data from four major economies, namely Canada, Japan, the UK and the US, which span the 1990:01–2011:12 period. The vast majority of studies employ linear Granger causality tests (Granger, 1969) when assessing the relationship between various macroeconomic variables despite the fact that there is clear evidence which points out to the existence of nonlinearities (e.g., Keynes, 1936; Shiller, 1993, 2005; Hiemstra and Jones, 1994; Shin et al., 2013; Choudhry et al., 2014). To our knowledge, no other study has applied nonlinear bivariate tests to assess the relationship between stock market volatility and the business cycle. Hence, our paper aims to fill this gap in the literature and to provide some fresh evidence.

Second, we extend previous empirical findings by exploring the impact of the recent financial crisis on the relationship between stock market volatility and the business cycle. This is an important aspect of the study which also serves as a robustness check during a period of heightened volatility. There is indeed evidence which suggests that stock market volatility is higher during recessions than during expansions, exhibiting a pronounced business cycle behaviour (see e.g., Officer, 1973; Schwert, 1989; Hamilton and Lin, 1996; Brandt and Kang, 2004; Mele, 2007). Hence, it is of particular interest to consider the impact of the recent financial crisis in our tests.

Third, we conduct a multivariate analysis in order to explore possible spillover effects within a cross-country framework. In this case, the stock market volatility and the business cycle of the US are incorporated into our model to assess the impact on the business cycle and the stock market volatility of the remaining three countries.[1] In addition to the linear multivariate causality tests, we adopt a recent test for nonlinear multivariate causality proposed by Bai et al. (2010). To our knowledge, this is the first study that follows a multivariate (both linear and nonlinear) approach in this context. As in the bivariate case, we also investigate the role of the financial crisis in our multivariate analysis.

Our main findings can be summarised as follows. Initially, we find significant bidirectional linear causality between the business cycle and stock market volatility in Canada and in the UK in the pre-crisis period. Interestingly, this result is unaffected or strengthened (depending on the direction) when we include the recent financial crisis in our sample. Moreover, the impact of the crisis is more pronounced in the causal relationship which runs from the business cycle to stock market volatility in Japan and in the US. Finally, both in the pre-crisis period and in the full sample period, stock market volatility significantly causes the business cycle in the US but not in Japan. When we assess causality by adopting a nonlinear framework, strong evidence supporting the existence of significant feedback (i.e. causality) is found in most cases. However, depending on the direction or the country, there are cases where the crisis either reveals nonlinearities or indicates the absence of nonlinear effects compared to the pre-crisis period.

Turning to our linear multivariate results, we find that the US indeed plays an important role as suggested by the existence of bidirectional causality between the US stock market volatility and business cycle and the corresponding variables of the remaining three countries. The results are in general robust to the inclusion of the crisis and in some cases the identified cross-country causal relationships become more significant. On the other hand, nonlinear multivariate tests show much stronger causality results for Canada and Japan when the crisis period is included. Especially in the case of Canada the impact of the crisis is more evident as we find significant causality results in both directions for all considered variables (i.e. there are nonlinear spillover effects between Canada and the US during the crisis). For Japan, we also identify a significant influence of the US variables as well as a significant effect of the crisis. This is an interesting finding given that the causality results between the Japanese stock market volatility and business cycle are much weaker in a bivariate setting. Regarding the UK, our multivariate tests indicate stronger nonlinear causality during the pre-crisis period. Nevertheless, the UK business cycle is significantly influenced by the US variables also during the crisis.

Finally, we employ both linear and nonlinear forecasting regressions and show that stock market volatility is an important short-term predictor of future economic activity (i.e. industrial production growth rate) within each country. Additionally, we find that the stock market volatility and the economic activity of the US are both significant predictors of the economic activity of the remaining countries suggesting a strong degree of market integration.

Overall, the results in this paper indicate the need for policy makers to take into consideration both cross-country spillover effects and nonlinearities when assessing the economic outlook of a specific country. This is particularly important in volatile periods of the stock market such as the recent financial crisis covered in our sample.

The remainder of the paper is organised as follows. Section 2 describes the data and provides some preliminary analysis. Section 3 presents the methodological approach and Section 4 discusses the empirical findings. Finally, Section 5 concludes.

## 2. Data description

We employ monthly data from four major economies, namely Canada, Japan, the UK and the US. Our dataset is derived from the Thomson Financial DataStream and covers the period between 1990:01 and 2011:12. The respective stock market indexes chosen to represent each country are the TSX composite index (Canada), the Nikkei 225 (Japan), the FTSE-All Share (UK) and the S&P 500 (US). The continuously compounded monthly stock returns are computed as follows:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

where $P_t$ and $P_{t-1}$ denote the stock index prices at time $t$ and $t-1$ respectively. For all countries, the total industrial production growth rate (i.e. log-changes of the total industrial production index) represents the business cycle and is obtained at a monthly frequency (seasonally adjusted). Fig. 1 shows the total industrial production index growth rate with respect to Canada, Japan, the US and the UK.

As it can be clearly observed, there is a pronounced decrease in the industrial production growth rate of all countries during the period of the recent financial crisis (shaded area) while it slowly bounces back during 2009 and onwards. This decrease in the growth rate of economic activity is much more evident in Japan where we observe an all time low around 2009 and 2011. These findings are consistent with recent evidence suggesting that the crisis has led to an important decline in the industrial production worldwide. For instance, Bartram and Bodnar (2009) mention that from a market capitalization of $51 trillion in world equity markets as of October 2007, share prices started to fall in early 2008 and this ultimately led to a massive decline in almost all indices by

[1] The findings of Cheung et al. (2009) indicate a contagion effect and a stronger interrelationship between the US and other markets such as the UK and Japan during the recent financial crisis.

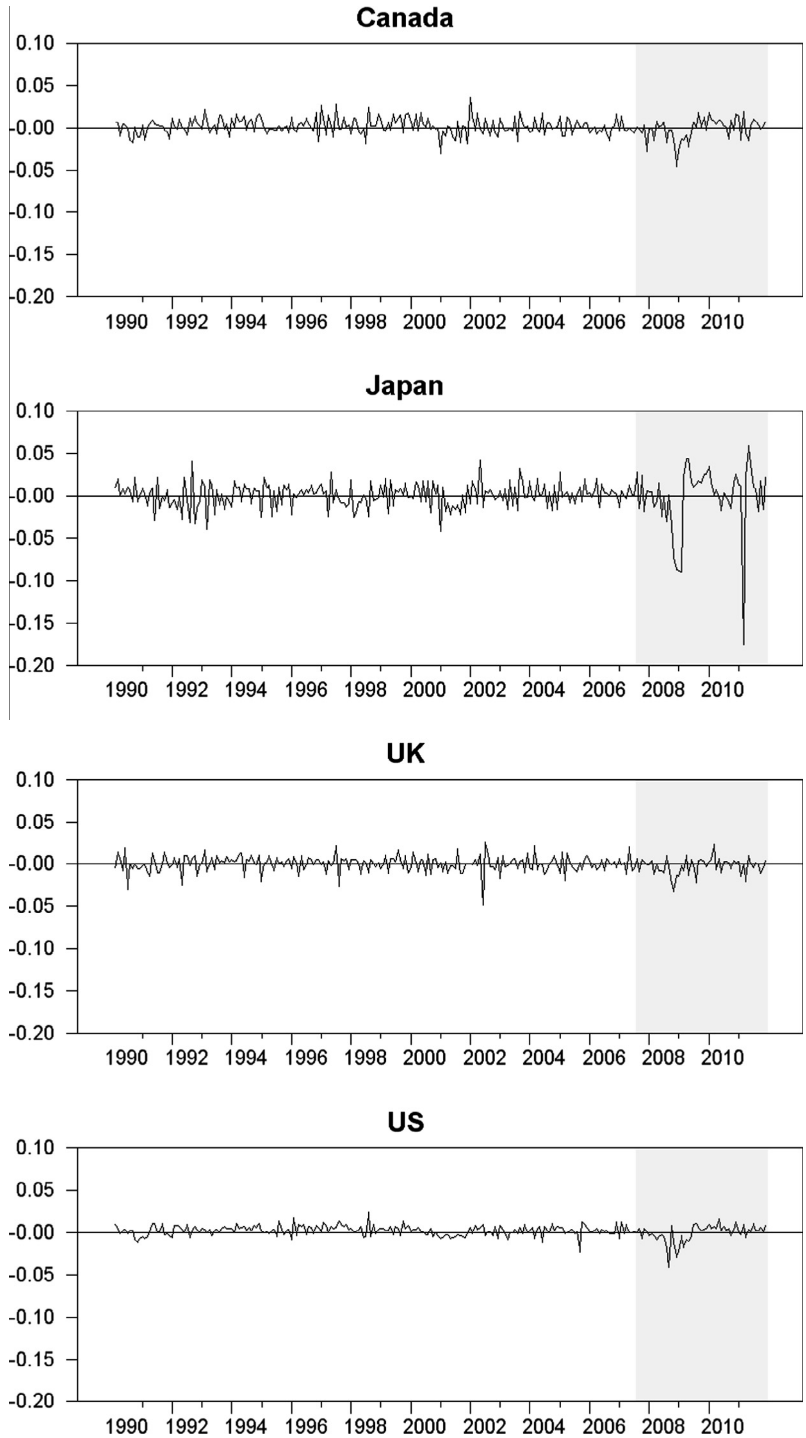


**Fig. 1.** Industrial production growth rate. This figure depicts the industrial production growth rate (in log terms) for all countries considered in our study covering the period between 1990:01 and 2011:12 (see Section 2.1 for further details).

30–40% between September 2008 and October 2008.[2] Therefore, it is important to investigate the impact of the financial crisis in our study and provide some new evidence. We shall return to this in the results section where we discuss in detail the effect of the crisis in the context of causality.

Moreover, in all markets under consideration the stock market volatility is estimated by means of the univariate GARCH(1,1) model. Fig. 2 depicts the estimated stock market volatilities during the total period of our sample. In line with previous studies which suggest that stock market volatility is higher during recessions than during expansions (e.g., Schwert, 1989, 2011; Hamilton and Lin, 1996; Brandt and Kang, 2004), we observe a sharp increase in volatility during the recent financial crisis (shaded area) in all markets under consideration.

Finally, unreported results based on the augmented Dickey and Fuller (1979) and the Kwiatkowski et al. (1992) (KPSS) unit root

[2] During that period, Lehman Brothers filed for bankruptcy while AIG was bailed out from the US government.

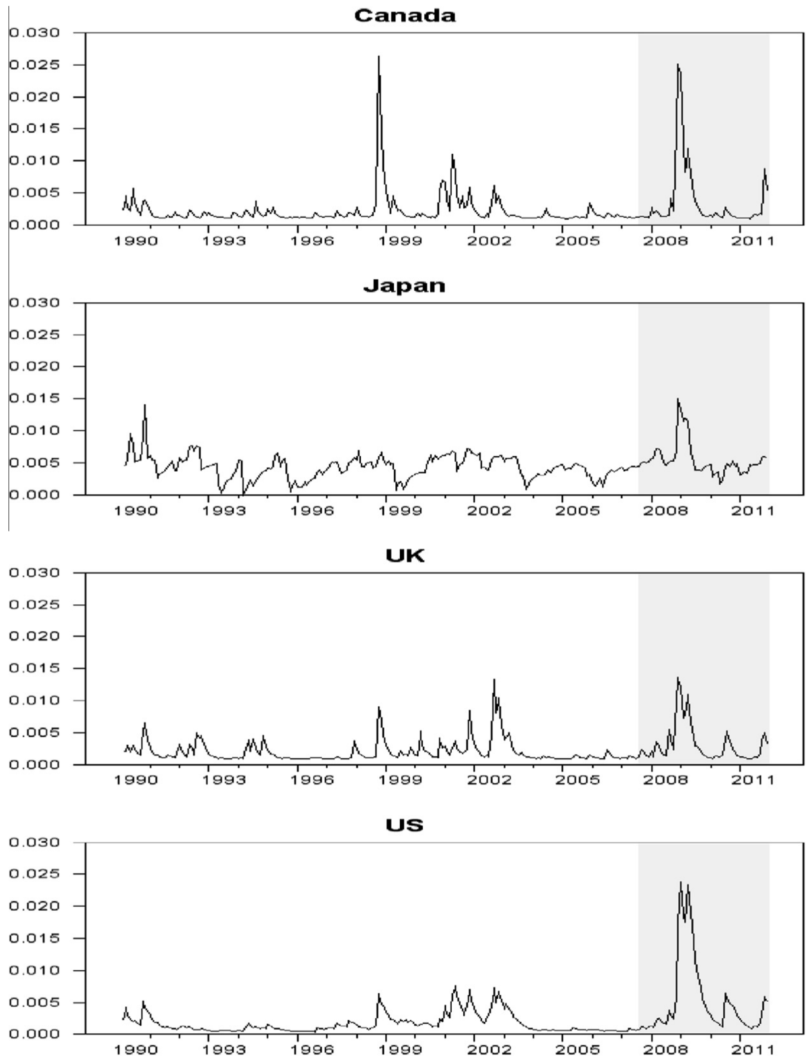


**Fig. 2.** Stock market volatility. This figure depicts the stock market volatility for all countries considered in our study covering the period between 1990:01 and 2011:12 (see Section 2.2 for further details).

tests show that the first differenced series, which we employ to test for linear and nonlinear causality, are stationary.[3]

## 3. Methodology

### 3.1. Bivariate and multivariate linear causality

In order to examine the linear relationship between stock market volatility and the business cycle indicator (i.e. the industrial production growth rate) within each market, we consider the widely accepted vector autoregression (VAR) specification and the corresponding Granger causality test (Granger, 1969). This approach enables us to assess whether there is a causal relationship between the variables in terms of time precedence. For instance, if variable $x_t$ Granger causes variable $y_t$, lags of $x_t$ can explain the current values of $y_t$. The specification of the applied bivariate VAR model can be expressed as follows:

$$x_t = \varphi_1 + \sum_{i=1}^{n} \alpha_i x_{t-i} + \sum_{i=1}^{n} \beta_i y_{t-i} + \varepsilon_{1t} \tag{2}$$

$$y_t = \varphi_2 + \sum_{i=1}^{n} \gamma_i x_{t-i} + \sum_{i=1}^{n} \delta_i y_{t-i} + \varepsilon_{2t} \tag{3}$$

where, in our case, $x_t$ is the stock market volatility (SV) in first differences, $y_t$ is the log-difference of industrial production (our business cycle indicator, BC), $n$ is the optimal lag length based on the well known information criteria such as the Akaike information criterion (AIC), and $\varepsilon_{1t}$ and $\varepsilon_{2t}$ are the residuals. Moreover, $\varphi_1$ and $\varphi_2$ are constants while the estimated coefficients $\alpha_i$, $\beta_i$, $\gamma_i$ and $\delta_i$, $i = 1,\ldots,n$, represent the linear relationship between variables $x_t$ and $y_{t.}$ To test for Granger causality, we are interested in the null hypothesis that the variable $y_t$ does not Granger cause $x_t$ which is rejected if the coefficients $\beta_i$ are jointly significantly different from zero. If $y_t$ Granger causes $x_t$, the past values of $y_t$ provide additional information on $x_t$. Similarly, the null hypothesis that $x_t$ does not Granger cause $y_t$ is rejected if the estimated coefficients $\gamma_i$ are jointly significantly different from zero. Finally, bidirectional causality exists if causality runs in both directions.

In this paper, we also examine linear causality in a multivariate setting with the aim to explore possible spillover effects among countries in either direction. Within this framework, we choose the US as the reference country since it represents the largest economy and it is probably the most influential both in economic and political terms. In particular, with respect to country *i* (i.e. Canada,

[3] The preliminary results including the GARCH diagnostics and the unit root tests are available upon request.

Japan or UK), we augment Eqs. (2) and (3) with the stock market volatility and the business cycle of the US ($SV_{US}$ and $BC_{US}$, respectively) and vice versa.

In the next sections we present the nonlinear approach adopted in our study and describe the relevant tests employed.

### 3.2. Bivariate nonlinear causality

Campbell and MacKinlay (1997, p.467) state that 'the strategic interactions among market participants, the process by which information is incorporated into security prices, and the dynamics of economy wide fluctuations are inherently nonlinear'. Additionally, as mentioned earlier, there is clear evidence indicating the existence of nonlinear features in various macroeconomic variables and relationships (see, Keynes, 1936; Kahneman and Tversky, 1979; Shiller, 1993, 2005; Hsieh, 1991, Barnett et al., 1997). Nonlinear causality was highlighted in the finance literature by Hiemstra and Jones (1994) and subsequent research papers have provided further evidence in a nonlinear setting with respect to various financial variables (e.g., Silvapulle and Choi, 1999; Chen and Wuh Lin, 2004; Diks and Panchenko, 2006; Bekiros and Diks, 2008a,b; Shin et al., 2013; Bekiros, 2014). Specifically, there are various factors such as transaction costs or information frictions which could give rise to nonlinearities and lead to non-convergence towards the long-run equilibrium. For example, Anderson (1997) argues that transaction costs are often ignored in studies of asset markets although in practice they could be substantial and prevent the adjustment of disequilibrium errors.[4] Anderson (1997) further shows that estimated models which consider these nonlinearities outperform their linear counterparts. Other sources that may be responsible for nonlinearities include 'diversity in agents' beliefs' (Brock and LeBaron, 1996), 'heterogeneity in investors' objectives arising from varying investment horizons and risk profiles' (Peters, 1994), and 'herd behaviour' (Lux, 1995). Given the above, it is clear that the need for nonlinear and asymmetric adjustments is imperative. Hence, in this study we also explore causality under a nonlinear framework.

Baek and Brock (1992) first developed a general non-parametric test for nonlinear Granger causality which was later modified by Hiemstra and Jones (1994).[5] To explore nonlinear causality between stock market volatility and industrial production within each country, we employ the Hiemstra and Jones (1994) test statistic. A description of the related methodological approach follows.

#### 3.2.1. Hiemstra and Jones (1994) test statistic

First, consider two strictly stationary and weakly dependent time series $\{X_t\}$ and $\{Y_t\}$, $t = 1,2,\ldots$. Denote the $m$-length lead vector of $X_t$ by $X_t^m$, and the $Lx$-length and $Ly$-length lag vectors of $X_t$ and $Y_t$, respectively, by $X_{t-Lx}^{Lx}$ and $Y_{t-Ly}^{Ly}$. That is,

$$\begin{aligned}
X_t^m &\equiv (X_t, X_{t+1}, \ldots, X_{t+m-1}), m = 1, 2\ldots, t = 1, 2, \ldots, \\
X_{t-Lx}^{Lx} &\equiv (X_{t-Lx}, X_{t-Lx+1}, \ldots, X_{t-1}), Lx = 1, 2, \ldots, t = Lx + 1, Lx + 2, \ldots, \\
Y_{t-Ly}^{Ly} &\equiv (Y_{t-Ly}, Y_{t-Ly+1}, \ldots, Y_{t-1}), Ly = 1, 2, \ldots, t = Ly + 1, Ly + 2, \ldots,
\end{aligned} \tag{4}$$

As stated in Hiemstra and Jones (1994), given values of $m$, $Lx$ and $Ly \geqslant 1$ and for $e \geqslant 0$, $Y$ does not strictly Granger cause $X$ if:

$$\begin{aligned}
&Pr\left(\|X_t^m - X_s^m\| < e \,|\, \|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\| < e, \|Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly}\| < e\right) \\
&= Pr\left(\|X_t^m - X_s^m\| < e \,|\, \|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\| < e\right)
\end{aligned} \tag{5}$$

In Eq. (5), $\Pr(\cdot)$ denotes probability and $\|\cdot\|$ denotes the maximum norm. The left hand side of Eq. (5) is the conditional probability that the distance between two arbitrary $m$-length lead vectors of $\{X_t\}$ is less than $e$, given that the distance between the corresponding $Lx$-length lag vectors of $\{X_t\}$ and $Ly$-length lag vectors of $\{Y_t\}$ is also less than $e$. The right hand side of Eq. (5) is the conditional probability that any two arbitrary $m$-length lead vectors of $\{X_t\}$ are within a distance $e$ of each other, given that their corresponding $Lx$-length lag vectors are also within a distance $e$ of each other. For all markets in our paper, $X_t$ is the stock market volatility and $Y_t$ is the business cycle represented by the industrial production growth rate. Therefore, if Eq. (5) is true, this implies that the business cycle does not Granger cause stock market volatility in nonlinear terms.

To implement a test based on Eq. (5), Hiemstra and Jones (1994) express the conditional probabilities in terms of the corresponding ratios of joint probabilities:

$$\frac{C1(m + Lx, Ly, e)}{C2(Lx, Ly, e)} = \frac{C3(m + Lx, e)}{C4(Lx, e)} \tag{6}$$

where $C1$, $C2$, $C3$, $C4$ are the joint probabilities.[6] For given values of $m$, $Lx$, and $Ly \geqslant 1$ and $e > 0$ under the assumption that $\{X_t\}$ and $\{Y_t\}$ are strictly stationary and weakly dependent, if $\{Y_t\}$ does not strictly Granger cause $\{X_t\}$ then,

$$\begin{aligned}
&\sqrt{n}\left(\frac{C1(m + Lx, Ly, e, n)}{C2(Lx, Ly, e, n)} - \frac{C3(m + Lx, e, n)}{C4(Lx, e, n)}\right) \\
&\to N(0, \sigma^2(m, Lx, Ly, e))
\end{aligned} \tag{7}$$

The appendix of Hiemstra and Jones (1994) provides further details regarding the definition and the estimator of the variance $\sigma^2(m, Lx, Ly, e)$.

Next, we turn to the approach we follow to examine causality within a nonlinear multivariate framework.

### 3.3. Multivariate nonlinear causality

In a recent study, Bai et al. (2010) extend the nonlinear causality test of Hiemstra and Jones (1994) and propose a nonlinear test in a multivariate setting. Hence, to complement the results of multivariate linear causality, we adopt the test developed by Bai et al. (2010) which will allow us to to capture potential nonlinearities between stock market volatility and the business cycle across countries. To our knowledge, no other study has examined possible spillover effects between stock market volatility and the business cycle following a nonlinear multivariate approach. Similar to the linear multivariate tests, the US is chosen as the reference country. Hence, the corresponding relationships linking stock market volatility and the business cycle within each country $i$ ($SV_i$ and $BC_i$, respectively) are extended with the stock market volatility and the business cycle of the US ($SV_{US}$ and $BC_{US}$, respectively).

In more detail, to test for nonlinear Granger causality between two variables, one has to apply a nonlinear causality test to the obtained stationary residual series from the linear Eqs. (2) and (3), $\{\hat{\varepsilon}_{1t}\}$ and $\{\hat{\varepsilon}_{2t}\}$. As stated in Bai et al. (2010), the same applies if we want to test for nonlinear causality between two vectors of time series (i.e. in a multivariate setting). The difference is that one has to estimate a VAR model of $n$ equations and obtain the corresponding residuals. Subsequently, a nonlinear Granger causality

[4] The theoretical evidence of nonlinear price adjustment with transaction costs can be traced back to Dumas (1992) who examined the dynamic process of the real exchange rate in spatially separated markets under proportional transactions costs. Also, Mishkin (1995) stresses the importance of transaction costs when analysing financial markets.

[5] Hiemstra and Jones (1994) test the relationship between stock returns and trading volume and their findings reveal significant bidirectional causality.

[6] For more details on these joint probabilities and on their corresponding correlation-integral estimators, see Hiemstra and Jones (1994).

test needs to be applied to the residual series instead of the original time series. For simplicity, let the corresponding residuals of two vectors of variables under examination to be defined as $X_t = (X_{1,t}, \ldots, X_{n_1,t})'$ and $Y_t = (Y_{1,t}, \ldots, Y_{n_2,t})'$. The $m_{x_i} - length$ lead vector and the $L_{x_i} - length$ lag vector of $X_{i,t}, i = 1, \ldots, n_1$, as well as the $m_{y_i} - length$ lead vector and the $L_{y_i} - length$ lag vector of $Y_{i,t}, i = 1, \ldots, n_2$, can be defined, respectively, as:

$$\begin{aligned}
X_{i,t}^{m_{x_i}} &\equiv (X_{i,t}, X_{i,t+1}, \ldots, X_{i,t+m_{x_i}-1}), m_{x_i} = 1, 2..., t = 1, 2, \ldots, \text{and} \\
X_{i,t-L_{x_i}}^{L_{x_i}} &\equiv (X_{i,t-L_{x_i}}, X_{i,t-L_{x_i}+1}, \ldots, X_{i,t-1}), L_{x_i} = 1, 2, \ldots, t = L_{x_i} + 1, L_{x_i} + 2, \ldots, \\
Y_{i,t}^{m_{y_i}} &\equiv (Y_{i,t}, Y_{i,t+1}, \ldots, Y_{i,t+m_{y_i}-1}), m_{y_i} = 1, 2 \ldots, t = 1, 2, \ldots, \text{and} \\
Y_{i,t-L_{y_i}}^{L_{y_i}} &\equiv (Y_{i,t-L_{y_i}}, Y_{i,t-L_{y_i}+1}, \ldots, Y_{i,t-1}), L_{y_i} = 1, 2, \ldots, t = L_{y_i} + 1, L_{y_i} + 2, \ldots,
\end{aligned} \tag{8}$$

Now we denote $M_x = (m_{x_1}, \ldots, m_{x_{n_1}}), L_x = (L_{x_1}, \ldots, L_{x_{n_1}}), m_x = \max(m_{x_1}, \ldots, m_{x_{n_1}})$, and $l_x = \max(L_{x_1}, \ldots, L_{x_{n_1}})$. $M_y, L_y, m_y$ and $l_y$ can be defined in the same way.

Similar to the bivariate case, Bai et al. (2010) show that the test statistic for nonlinear Granger causality is of the following form under the null hypothesis no Granger causality:

$$\sqrt{n}\left(\frac{C1(M_x + Lx, Ly, e, n)}{C2(Lx, Ly, e, n)} - \frac{C3(M_x + Lx, e, n)}{C4(Lx, e, n)}\right) \to N(0, \sigma^2(M_x, Lx, Ly, e)) \tag{9}$$

where $C1$, $C2$, $C3$, $C4$ are joint probabilities.[7]

In the next section, we turn to the discussion of our empirical results.

## 4. Empirical results

### 4.1. Bivariate linear causality results

Table 1 shows the results of the bivariate linear causality (described in Section 3.1) between the business cycle and the stock market volatility for all markets under consideration. Panel I presents the results with respect to the pre-crisis period (1990:01–2007:06), while Panel II presents the corresponding results for the full sample period (i.e. 1990:01–2011:12). The results in Panel II enable us to assess the impact of the crisis which is a period of heightened volatility and serves as a useful robustness check.

Panel I suggests that there is a significant causal relationship which runs from the business cycle to stock market volatility in Canada and in the UK at the 5% and 10% conventional levels, respectively. However, no such relationship is detected in the case of the US and Japan. Similar findings for Canada are reported in Binswanger (2001). Moreover, our results for Japan are in line with Ahn and Lee (2006) who find no significant relationship, and Binswanger (2001) who indicates that the relationship between Japanese stock returns and real economic activity has broken down since 1980 s. On the other hand, we find that stock market volatility significantly causes the business cycle in the US (at the 1% level), in Canada (at the 5% level) and in the UK (at the 10% level). Our findings regarding bidirectional linear causality in the UK are slightly stronger than the ones in Errunza and Hogan (1998) and Morelli (2002) who report no causality between stock market volatility and macroeconomic factors for the UK. Finally, there are several studies which report similar findings for the US using different data periods and empirical settings (Schwert, 1989; Lee, 1992; Campbell et al., 2001; Ahn and Lee, 2006; Bloom et al., 2014; Rahman, 2009; Fornari and Mele, 2013).

Turning to the results in Panel II, we observe that there is a significant impact of the crisis on the dynamics between stock market volatility and the business cycle. Overall, we find stronger causal relationships in either direction when the crisis is included in our sample. Specifically, we now find significant unidirectional causality which runs from the business cycle to stock market volatility in the US and in Japan at the 5% and 10% levels of significance, respectively. In the case of the UK, the significance of this relationship strengthens from 10% to 1% while in Canada it remains unaltered (at the 5% level).

Our results for the US conform to the arguments presented in a few previous studies. For instance, Bernanke's (1983) study of Great depression reports that the financial crisis causes financial losses that intensify recession in the economy. Schwert (1990a) finds that the stock market is very sensitive to the financial crisis and stock market volatility rises during this period. Finally, Campbell et al. (2001) find that stock market volatility significantly increases during economic downturns and leads recession.

Regarding unidirectional causality from stock market volatility to the business cycle, the results in Panel II suggest that the inclusion of the financial crisis leads to stronger relationships in the case of Canada (from 5% to 1%) and in the UK (from 10% to 5%). Moreover, as in the pre-crisis period, stock market volatility significantly causes the business cycle in the US at the 1% level while no significant evidence is found with respect to Japan. Our results in the UK market indicate that in recent years the relationship between stock market volatility and the business cycle might have become somewhat stronger. For example, earlier studies such as Errunza and Hogan (1998) and Morelli (2002) find no significant causal relationship between macroeconomic factors such as industrial production, money supply or inflation and stock market volatility in the UK context. Additionally, our findings are in line to Binswanger (2001) who finds a significant feedback (i.e. causality) between stock market volatility and the business cycle in Canada. On the other hand, the absence of a significant relationship in Japan in nearly all sample periods we consider is consistent with the previous literature (see, Ahn and Lee, 2006; and Binswanger (2001)). One possible explanation for this could be that unlike the economies of the other countries we consider, the Japanese economy has experienced more periods of recession which were also longer in duration compared to the expansionary phases. This can be clearly seen in Fig. 1. Additionally, the Japanese results may indicate the failure of linear tests to capture the relationship between stock market volatility and the business cycle. Therefore, as stressed earlier, we also adopt a nonlinear approach in this paper to further examine the issue.

### 4.2. Bivariate nonlinear causality results

This section extends the previous findings and discusses the results under a nonlinear causality framework based on the Hiemstra and Jones (1994) test statistic which was discussed in Section 3.2. Panel I of Table 2 tabulates the results with respect to the pre-crisis period (i.e. 1990:01–2007:06). On the other hand, Panel II of Table 2 shows the results for the full sample which includes the recent financial crisis and serves as a robustness check.

During the pre-crisis period, the computed Hiemstra and Jones (1994) test statistics suggest that there is a significant nonlinear causal relationship which runs from stock market volatility to the business cycle in all countries under consideration. Evidence of causality from the business cycle to stock market volatility is found only in the UK and hence, this is the only case where we identify bidirectional nonlinear causality.

[7] For more details on the corresponding correlation-integral estimators for the joint probabilities in Eq. (9), see Bai et al. (2010). For a full proof and the details on the consistent estimator of the variance of the test statistic, see also Bai et al. (2010).

**Table 1**
Bivariate linear causality between stock market volatility and the business cycle.

| Country | Business cycle → Stock market volatility | | | | Stock market volatility → Business cycle | | | |
|---|---|---|---|---|---|---|---|---|
| | Canada | Japan | UK | US | Canada | Japan | UK | US |
| *Panel I: Pre-crisis period (1990:01–2007:06)* | | | | | | | | |
| Lags BC-SMV | 11–8 | 6–11 | 11–7 | 12–4 | 4–9 | 6–2 | 9–8 | 12–1 |
| *F*-Stat | 2.060** | 0.900 | 1.820* | 0.539 | 2.000** | 1.340 | 1.930* | 13.960*** |
| Adj. $R^2$ | 0.163 | 0.070 | 0.186 | 0.047 | 0.063 | 0.174 | 0.159 | 0.124 |
| SSE | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| RSS | 0.001 | 0.000 | 0.000 | 0.001 | 0.014 | 0.028 | 0.011 | 0.005 |
| RESET | 1.130 | 1.200 | 1.440 | 3.395 | 3.650 | 1.700 | 2.040 | 0.320 |
| White | 197.000 | 182.170 | 193.350 | 187.910 | 120.580 | 56.350 | 173.180 | 98.920 |
| LB | 2.942 | 12.840 | 5.738 | 0.936 | 8.897 | 14.623 | 1.729 | 2.910 |
| JB | 2.950 | 10.750 | 1.922 | 2.787 | 2.006 | 3.121 | 5.518 | 2.504 |
| *Panel II: Full sample period (1990:01–2011:12)* | | | | | | | | |
| Lags BC-SV | 10–10 | 7–11 | 11–10 | 7–12 | 9–9 | 3–9 | 5–9 | 11–11 |
| *F*-Stat | 2.190** | 1.690* | 2.710*** | 2.060** | 3.120*** | 1.390 | 2.080** | 2.800*** |
| Adj. $R^2$ | 0.110 | 0.131 | 0.131 | 0.331 | 0.171 | 0.035 | 0.050 | 0.249 |
| SSE | 0.000 | 0.000 | 0.000 | 0.000 | 0.008 | 0.005 | 0.010 | 0.003 |
| RSS | 0.001 | 0.000 | 0.000 | 0.000 | 0.018 | 0.107 | 0.020 | 0.008 |
| RESET | 1.781 | 5.983 | 1.790 | 87.084 | 1.039 | 5.390 | 2.060 | 3.930 |
| White | 245.900 | 208.200 | 251.300 | 235.500 | 210.500 | 188.100 | 135.700 | 260.970 |
| LB | 2.500 | 8.060 | 5.460 | 6.220 | 2.350 | 9.120 | 12.560 | 0.767 |
| JB | 2.580 | 14.400 | 1.710 | 5.880 | 3.370 | 5.850 | 2.520 | 9.240 |

This table presents the results of the bivariate linear causality tests, described in Section 3.1, between stock market volatility and the business cycle (represented by the industrial production growth rate) for all countries under consideration. Panel I shows the results with respect to the pre-crisis period while Panel II shows the results with respect to the full sample period and assesses the impact of the recent financial crisis. Asterisks ***, ** and * denote significance at the 1%, 5% and 10% conventional levels respectively. BC: business cycle represented by the industrial production growth rate; SV: stock market volatility; SSE: Standard error of estimate squared; RSS: Residual sum of squares; Reset: Ramsey's Specification Test; White: White's Heteroskedasticity Test; LB: Ljung and Box (1978) test for autocorrelation including up to 12 lags; JB: Jarque–Bera normality of residuals test.

**Table 2**
Bivariate nonlinear causality tests between stock market volatility and the business cycle.

| Country | Stock market volatility → Business cycle HJ Test-Stat | Business cycle → Stock market volatility HJ Test-Stat |
|---|---|---|
| *Panel I: Pre-crisis period (1990:01–2007:06)* | | |
| Canada | 1.798** | −1.124 |
| Japan | 1.591* | 1.128 |
| UK | −1.332* | −1.361* |
| US | −2.117** | −0.719 |
| *Panel II: Full sample period (1990:01–2011:12)* | | |
| Canada | 1.801** | −2.011** |
| Japan | 1.023 | 2.594** |
| UK | −1.568* | 1.429* |
| US | 0.046 | 0.588 |

This table presents the results of the Hiemstra and Jones (1994) test statistic (HJ) described in Section 3.2 which tests for nonlinear causality between stock market volatility and the business cycle (represented by the industrial production growth rate), for all countries under consideration. Panel I shows the results during the pre-crisis period while Panel II shows the corresponding results for the full sample and assesses the impact of the recent financial crisis. Asterisks ***, ** and * denote significant nonlinear causality at the 1%, 5% and 10% levels, respectively.

When we include the financial crisis in the sample (Table 2, Panel II), we still find evidence of causality from stock market volatility to the business cycle in the cases of Canada and the UK. However no such evidence is found in Japan and the US suggesting that the crisis led to the disappearance of nonlinear effects in these countries. On the other hand, the computed Hiemstra and Jones (1994) statistics indicate that the impact of the crisis under a nonlinear framework is more evident in the causal relationship which runs from the business cycle to stock market volatility. As mentioned earlier, such significant relationship during the pre-crisis period is detected only in the case of the UK. However, the inclusion of the crisis leads to stronger results and additionally reveals significant nonlinear effects in Canada and in Japan. Hence, during the crisis period both the UK and Canada show bidirectional nonlinear causality. Finally, no evidence of nonlinear causality is found with respect to the US in this case.

### 4.3. Multivariate causality results

In this section, we discuss the results of both linear and nonlinear multivariate causality explained, respectively, in Sections 3.1 and 3.3. As stressed earlier, most studies focus on bivariate causality and, to our knowledge, no other evidence exists regarding stock market volatility and the business cycle in either a linear or a nonlinear multivariate setting across countries. In order to explore the issue in our study, the bivariate models of causality for Canada, Japan and the UK are extended by including the stock market volatility and the business cycle of the US. The reason why we choose the US is because it is the largest economy among the rest of the developed countries, the one with great political influence and also the epicentre of the recent global financial crisis. Hence, our goal is to investigate and identify possible spillover effects among the US and the remaining countries in our sample. Similar to our bivariate analysis, we also explore the effect of the crisis as a robustness check in the multivariate approach.

#### 4.3.1. Multivariate linear causality results

This section presents the results of our multivariate analysis within a linear setting (see Section 3.1) and aims to identify possible spillover effects between stock market volatility and the business cycle across countries. As in the bivariate tests, our multivariate analysis is also carried out based on two sample lengths; The first one spans the pre-crisis period (1990:01–2007:06) and the second includes the financial crisis period and explores its impact (i.e. 1990:01–2011:12). The results for these periods are tabulated in Tables 3 and 4, respectively.

As it can be observed in Table 3, there is a significant feedback from the US stock market volatility ($SV_{US}$) and business cycle ($BC_{US}$) to the Canadian stock market volatility ($SV_{CAN}$) at the 5% significance level. The same result holds in the direction from Canada to the US and hence, the corresponding Canadian variables (i.e.

$SV_{CAN}$ and $BC_{CAN}$) are significant predictors of the US stock market volatility. On the other hand, the US business cycle is significantly causing the Canadian business cycle at the 1% level but the US stock market volatility is not significant in this case. Finally, both $SV_{CAN}$ and $BC_{CAN}$ are significantly causing the US business cycle (at the 5% and 1% significance levels, respectively). Moreover, a mutual interdependence among all considered variables is also revealed within a cross-country framework between the US and Japan (at varying significance levels between 1% and 10%). This is a very interesting finding given that earlier we reported weak evidence of causality between the Japanese stock market volatility and business cycle in a bivariate setting. However, these variables are found to be strongly influenced and bear influence on the corresponding US variables under a multivariate testing framework suggesting significant spillover effects between the two countries. This could be explained by the integration between the equity markets of the US and Japan (for evidence of integration, see Hamao et al., 1990; Koutmos and Booth, 1995).

A similar picture arises when we consider the interaction between the UK and the US markets. Specifically, we can observe significant causal relationships and bidirectional spillover effects across these two countries. Therefore, our results suggest that within a multivariate setting the stock market volatility and the business cycle of the US are important explanatory variables which cause the stock market volatility and the business cycle of the UK (and vice versa). These results are broadly consistent with Kanas and Ioannidis (2010) who find that US stock returns together with UK stock returns significantly cause the output growth rate of the UK. Consequently, they state that the US stock returns contain important information which is reflected on the relationship between the UK variables.

The tabulated results in Table 4 suggest that there are still significant spillover effects when we extend our sample to include the recent financial crisis. More specifically, the influence of the US stock market volatility and business cycle on the Canadian stock market volatility remains robust and significant at the 5% level. On the other hand, in contrast to the pre-crisis period the stock market volatility of the US is now significantly causing the Canadian business cycle while the US business cycle remains significant at the 1% level in this case. These findings reveal a somewhat stronger overall influence of the US on Canada during a period of higher than usual volatility. Moreover, regarding potential spillover effects from Canada to the US, we generally observe similar results to the pre-crisis period. In particular, with the exception of the Canadian business cycle which is no longer found to significantly cause the US stock market volatility, the Canadian variables possess significant explanatory power for the corresponding US variables.

With respect to the interaction between Japan and the US, the results show a stronger influence of the US on the Japanese business cycle but not on the Japanese stock market volatility. Interestingly, we identify a significant feedback from the Japanese stock market volatility and business cycle to the US stock market volatility. In addition, the Japanese business cycle causes the US one but the Japanese stock market volatility is insignificant in this context. These relatively weaker results of multivariate causality among Japan and the US during the crisis may indicate that a nonlinear testing framework is required to better capture potential spillover effects. This is further investigated in the next section.

Finally, Table 4 reveals that the evidence of causality and spillover effects across the UK and the US remains significant when we add the crisis to the sample. This finding suggests that these two economies are strongly associated both during periods with normal levels of stock market volatility as well as during periods with heightened volatility such as the recent financial crisis.

**Table 3**
Multivariate linear causality between stock market volatility and the business cycle: pre-crisis period (1990:01–2007:06).

| Country | Canada | | | US | | |
|---|---|---|---|---|---|---|
| Dependent variable | Stock market volatility | | | Stock market volatility | | |
| Independent variables | $BC_{CAN}$ | $SV_{US}$ | $BC_{US}$ | $BC_{US}$ | $SV_{CAN}$ | $BC_{CAN}$ |
| Lags | 5 | 2 | 4 | 1 | 11 | 2 |
| *F*-Stat | 2.25** | 3.44** | 2.51** | 3.93** | 2.87** | 3.46** |
| Dependent variable | Business cycle | | | Business cycle | | |
| Independent variables | $SV_{CAN}$ | $SV_{US}$ | $BC_{US}$ | $SV_{US}$ | $SV_{CAN}$ | $BC_{CAN}$ |
| Lags | 9 | 5 | 1 | 5 | 7 | 3 |
| *F*-Stat | 2.37** | 0.96 | 11.30*** | 3.95*** | 3.20** | 4.30*** |
| Country | Japan | | | US | | |
| Dependent variable | Stock market volatility | | | Stock market volatility | | |
| Independent variables | $BC_{JP}$ | $SV_{US}$ | $BC_{US}$ | $BC_{US}$ | $SV_{JP}$ | $BC_{JP}$ |
| Lags | 2 | 1 | 6 | 6 | 3 | 2 |
| *F*-Stat | 3.02** | 0.27 | 2.81** | 2.34** | 4.50*** | 2.37** |
| Dependent variable | Business cycle | | | Business cycle | | |
| Independent variables | $SV_{JP}$ | $SV_{US}$ | $BC_{US}$ | $SV_{US}$ | $SV_{JP}$ | $BC_{JP}$ |
| Lags | 9 | 10 | 5 | 3 | 11 | 1 |
| *F*-Stat | 2.30** | 4.76*** | 1.99* | 3.81** | 2.01* | 11.01*** |
| Country | UK | | | US | | |
| Dependent variable | Stock market volatility | | | Stock market volatility | | |
| Independent variables | $BC_{UK}$ | $SV_{US}$ | $BC_{US}$ | $BC_{US}$ | $SV_{UK}$ | $BC_{UK}$ |
| Lags | 5 | 11 | 6 | 6 | 3 | 4 |
| *F*-Stat | 2.27** | 2.45** | 2.08* | 2.64** | 7.27*** | 3.27** |
| Dependent variable | Business cycle | | | Business cycle | | |
| Independent variables | $SV_{UK}$ | $SV_{US}$ | $BC_{US}$ | $SV_{US}$ | $SV_{UK}$ | $BC_{UK}$ |
| Lags | 7 | 10 | 3 | 9 | 1 | 4 |
| *F*-Stat | 2.03* | 1.99* | 5.75*** | 1.99* | 3.74** | 4.23*** |

This table presents the results of multivariate linear causality (described in Section 3.1) between the stock market volatility and the business cycle (represented by the industrial production growth rate) of each country considered in our sample and the corresponding variables of the US during the pre-crisis period (i.e. 1990:01–2007:06). Asterisks ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

**Table 4**
Multivariate linear causality between stock market volatility and the business cycle: full sample period (1990:01–2011:12).

| Country | Canada | | | US | | |
|---|---|---|---|---|---|---|
| Dependent variable | Stock market volatility | | | Stock market volatility | | |
| Independent variables | $BC_{CAN}$ | $SV_{US}$ | $BC_{US}$ | $BC_{US}$ | $SV_{CAN}$ | $BC_{CAN}$ |
| Lags | 5 | 2 | 4 | 1 | 11 | 2 |
| *F*-Stat | 2.25** | 3.43** | 2.51** | 3.93** | 1.88** | 1.73 |
| Dependent variable | Business cycle | | | Business cycle | | |
| Independent variables | $SV_{CAN}$ | $SV_{US}$ | $BC_{US}$ | $SV_{US}$ | $SV_{CAN}$ | $BC_{CAN}$ |
| Lags | 12 | 1 | 4 | 1 | 11 | 2 |
| *F*-Stat | 1.67*** | 2.90*** | 3.50*** | 3.95*** | 3.39*** | 6.40*** |
| Country | Japan | | | US | | |
| Dependent variable | Stock market volatility | | | Stock market volatility | | |
| Independent variables | $BC_{JP}$ | $SV_{US}$ | $BC_{US}$ | $BC_{US}$ | $SV_{JP}$ | $BC_{JP}$ |
| Lags | 6 | 3 | 1 | 6 | 1 | 2 |
| *F*-Stat | 1.95* | 0.89 | 0.06 | 2.29** | 6.10*** | 2.44** |
| Dependent variable | Business cycle | | | Business cycle | | |
| Independent variables | $SV_{JP}$ | $SV_{US}$ | $BC_{US}$ | $SV_{US}$ | $SV_{JP}$ | $BC_{JP}$ |
| Lags | 1 | 10 | 3 | 4 | 1 | 6 |
| *F*-Stat | 4.06** | 4.41*** | 3.24** | 3.23** | 1.75 | 2.06* |
| Country | UK | | | US | | |
| Dependent variable | Stock market volatility | | | Stock market volatility | | |
| Independent variables | $BC_{UK}$ | $SV_{US}$ | $BC_{US}$ | $BC_{US}$ | $SV_{UK}$ | $BC_{UK}$ |
| Lags | 5 | 3 | 6 | 6 | 3 | 4 |
| *F*-Stat | 2.27** | 5.29*** | 2.33** | 2.64** | 7.27*** | 3.27** |
| Dependent variable | Business cycle | | | Business cycle | | |
| Independent variables | $SV_{UK}$ | $SV_{US}$ | $BC_{US}$ | $SV_{US}$ | $SV_{UK}$ | $BC_{UK}$ |
| Lags | 4 | 9 | 3 | 9 | 1 | 4 |
| *F*-Stat | 2.49** | 2.75** | 6.89*** | 1.90* | 3.74* | 4.23*** |

This table presents the results of linear multivariate causality (described in Section 3.1) between the stock market volatility and the business cycle (represented by the industrial production growth rate) of each country considered in our sample and the corresponding variables of the US during the full sample which includes the recent financial crisis (i.e. 1990:01–2011:12). Asterisks ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

#### 4.3.2. Multivariate nonlinear causality results

This section further explores Granger causality within a cross-country framework by adopting a nonlinear approach based on the recently developed test by Bai et al. (2010) which was described in Section 3.3. In particular, we extend the nonlinear bivariate tests within each country (Canada, Japan or the UK) by including the stock market volatility and the business cycle of the US. Therefore, we are interested in potential spillover effects and test for joint causality in a nonlinear setting which might better capture the relationship among the considered variables. The results are tabulated in Table 5. Panel I is related to the pre-crisis period while panel II shows the corresponding results for the full sample and allows us to assess the impact of the crisis.

Starting from the pre-crisis period, the computed statistics in Panel I of Table 5 suggest that the Canadian stock market volatility is jointly caused by the Canadian and US business cycle and the US stock market volatility at the 5% conventional level. However, no evidence of causality is found in any other case between these two countries. Interestingly, when we look at the relationship between the Japanese and the US variables, the only evidence of nonlinear multivariate causality indicates that the Japanese business cycle and stock market volatility and the US stock market volatility jointly cause the US business cycle at the 5% significance level. This identified nonlinear association affecting the US economic activity suggests that any strategy or policy related to the US economy should take into consideration the impact of Japanese real economic activity and stock market volatility among the key determinant variables. Finally, a much stronger link is revealed between the UK and the US. Specifically, both the UK business cycle and stock market volatility are influenced by the corresponding US variables. On the other hand, the US stock market volatility is also caused by the UK variables while no evidence of joint

**Table 5**
Multivariate nonlinear causality between stock market volatility and the business cycle.

| Country | Dependent variable | Independent variables | Test statistic |
|---|---|---|---|
| *Panel I: Pre-crisis period (1990:01–2007:06)* | | | |
| Canada | $SV_{CAN}$ | $BC_{CAN}$, $SV_{US}$, $BC_{US}$ | 1.429* |
| | $BC_{CAN}$ | $SV_{CAN}$, $SV_{US}$, $BC_{US}$ | 0.553 |
| | $SV_{US}$ | $SV_{CAN}$, $BC_{CAN}$, $BC_{US}$ | 1.044 |
| | $BC_{US}$ | $SV_{CAN}$, $BC_{CAN}$, $SV_{US}$ | 0.638 |
| Japan | $SV_{JP}$ | $BC_{JP}$, $SV_{US}$, $BC_{US}$ | 0.230 |
| | $BC_{JP}$ | $SV_{JP}$, $SV_{US}$, $BC_{US}$ | 0.426 |
| | $SV_{US}$ | $SV_{JP}$, $BC_{JP}$, $BC_{US}$ | 0.247 |
| | $BC_{US}$ | $SV_{JP}$, $BC_{JP}$, $SV_{US}$ | 2.132** |
| UK | $SV_{UK}$ | $BC_{UK}$, $SV_{US}$, $BC_{US}$ | 1.469* |
| | $BC_{UK}$ | $SV_{UK}$, $SV_{US}$, $BC_{US}$ | 1.514* |
| | $SV_{US}$ | $SV_{UK}$, $BC_{UK}$, $BC_{US}$ | 2.380** |
| | $BC_{US}$ | $SV_{UK}$, $BC_{UK}$, $SV_{US}$ | 0.773 |
| *Panel II: Full sample period (1990:01–2011:12)* | | | |
| Canada | $SV_{CAN}$ | $BC_{CAN}$, $SV_{US}$, $BC_{US}$ | 2.193** |
| | $BC_{CAN}$ | $SV_{CAN}$, $SV_{US}$, $BC_{US}$ | 1.698** |
| | $SV_{US}$ | $SV_{CAN}$, $BC_{CAN}$, $BC_{US}$ | 1.818** |
| | $BC_{US}$ | $SV_{CAN}$, $BC_{CAN}$, $SV_{US}$ | 1.368* |
| Japan | $SV_{JP}$ | $BC_{JP}$, $SV_{US}$, $BC_{US}$ | 2.310*** |
| | $BC_{JP}$ | $SV_{JP}$, $SV_{US}$, $BC_{US}$ | 2.767*** |
| | $SV_{US}$ | $SV_{JP}$, $BC_{JP}$, $BC_{US}$ | 2.967*** |
| | $BC_{US}$ | $SV_{JP}$, $BC_{JP}$, $SV_{US}$ | 1.287 |
| UK | $SV_{UK}$ | $BC_{UK}$,$SV_{US}$, $BC_{US}$ | 0.262 |
| | $BC_{UK}$ | $SV_{UK}$, $SV_{US}$, $BC_{US}$ | 2.172** |
| | $SV_{US}$ | $SV_{UK}$, $BC_{UK}$, $BC_{US}$ | 0.137 |
| | $BC_{US}$ | $SV_{UK}$, $BC_{UK}$, $SV_{US}$ | 0.638 |

This table presents the results of multivariate nonlinear causality based on the Bai et al. (2010) test (see Section 3.2) between stock market volatility and the business cycle (represented by the industrial production growth rate) within a cross-country framework. Panel I presents the results during the pre-crisis period while Panel II is related to the full sample which includes the recent financial crisis. $BC_i$ and $SV_i$ denote, respectively, the business cycle and stock market volatility of country $i$, where $i$ can be Canada, Japan, UK or the US. Asterisks ***, ** and * denote significant joint causality at the 1%, 5% and 10% conventional levels respectively.

nonlinear causality is found when the US business cycle is the dependent variable.

Turning to Panel II of Table 5 which shows the full sample period results, we observe a much stronger nonlinear interdependence among the Canadian and the US variables compared to the pre-crisis period. Therefore, the crisis has led to a higher degree of association between these two economies. Also, this finding may be an indication that a nonlinear framework can better capture cross-country spillover effects in some cases. The impact of the financial crisis is also evident when we examine multivariate nonlinear causality between Japan and the US. In contrast to the pre-crisis period, we now find significant spillover effects from the US variables to the Japanese ones at the 1% level. The stock market volatility of the US is also significantly influenced by the Japanese business cycle and stock market volatility (along with the US business cycle). However, we no longer find evidence of significant feedback from Japan to the US business cycle in this case. Finally, the stock market volatility and the business cycle of the US (jointly with the UK stock market volatility) cause the UK business cycle at the 5% significance level. This result implies a strong influence of the US on the UK economic outlook which is nonlinear in nature. Nevertheless, this is the only significant relationship we identify during the crisis between the UK and the US suggesting less nonlinear spillover effects overall between the two countries in this period.

### 4.4. Robustness checks and further empirical evidence

#### 4.4.1. Macroeconomic volatility and stock market volatility

To delve deeper into the relationship between stock market volatility and economic activity, we additionally explored the links between stock market volatility and macroeconomic volatility (i.e. the volatility of the industrial production growth rate).[8] Overall, our results are qualitatively similar to the ones presented in our previous main analysis. For example, we find a strong bidirectional relationship between stock market volatility and macroeconomic volatility in the UK in all periods. Moreover, some evidence of causality is found in Canada and in the US while the weakest evidence is observed in Japan, a finding which is consistent with our previous results. In some cases, the recent financial crisis is found to have some impact and to strengthen some relationships (e.g., in Canada and the US). Regarding the multivariate case, we identify that the US plays a significant role is this context and this is particularly evident in the case of Canada. Finally, no significant evidence is found in a nonlinear setting suggesting that the linear model specification is adequately capturing the relationship between stock market volatility and the volatility of economic activity.

#### 4.4.2. Linear and nonlinear forecasting regressions

This section provides additional empirical evidence and explores the relative role of stock market volatility as a short-term predictor of real economic activity in all markets under consideration.[9] Therefore, it complements the results of Granger causality and serves as a useful robustness check. To this end, we initially focus on the following forecasting regression:

$$y_{t+h} = \alpha + \beta x_t + \gamma' Z_t + \sum_{i=0}^{p} \rho_i y_{t-i} + \varepsilon_{t+h} \tag{10}$$

where $y_{t+h}$ denotes the change in economic activity (i.e. the industrial production growth rate), $y_{t+h} = \frac{1200}{h+1} \ln(\frac{Y_{t+h}}{Y_t}), h > 0$ is the forecast horizon, $x_t$ is the stock market volatility (SV) in first differences, $Z_t$ is a vector of other financial indicators that may contain useful information about future economic activity such as the term spread or the real Treasury yield, and $\varepsilon_{t+h}$ is the error term. Given that one of our objectives is to investigate the role of the US on the economic activity of the other markets, $Z_t$ also incorporates the stock market volatility and economic activity of the US when Eq. (10) is estimated with respect to Canada, Japan and the UK. The null hypothesis of no predictability, in terms of stock market volatility, is that $\beta$ equals zero in Eq. (10), while the alternative hypothesis of predictability predicates that $\beta \neq 0$. To assess the robustness of the results, this forecasting exercise is first performed when the information content of the relevant financial indicators is absent (i.e. $Z_t = \emptyset$) and then when it is included via $Z_t$. The corresponding results when $h = 1$ are presented in Table 6.[10]

We observe that stock market volatility is a significant short-term predictor of the economic activity in all countries under consideration. When we include $Z_t$ into the model to account for additional financial indicators, this result remains unaffected establishing the important role of stock market volatility on predicting future economic activity. Furthermore, our findings based on this model specification reveal that the stock market volatility and economic activity of the US are also significant short-term predictors of the economic activity of the remaining markets.[11]

Given the strong evidence of nonlinear features documented in the previous sections, we extend the forecasting approach presented above and offer evidence based on a nonlinear forecasting model which allows us to further explore the relationship between economic activity and stock market volatility. Within this context, we adopt the class of smooth-transition threshold (STR) models (see, *inter alia*, Chan and Tong, 1986; Teräsvirta and Anderson, 1992; Granger and Teräsvirta, 1993; Teräsvirta, 1994; McMillan, 2003). In contrast to simple threshold models which impose an abrupt change in parameter values, STR models allow for the transition between different regime states to be smooth. The threshold model can be expressed as follows:

$$\begin{aligned} y_{t+h} = {} & \alpha + \beta x_t + \gamma' Z_t + \sum_{i=0}^{p} \rho_i y_{t-i} \\ & + \left( \varphi_0 + \varphi_1 x_t + \varphi_2' Z_t + \sum_{i=0}^{p} \theta_i y_{t-i} \right) F(y_{t-d}) + \varepsilon_{t+h} \end{aligned} \tag{11}$$

where all variables are defined as in Eq. (10) while $F(y_{t-d})$ is the transition function and $y_{t-d}$ is the transition variable. Following the literature, the first form of transition function we consider is the logistic function which is shown in Eq. (12) (see also, Chan and Tong, 1986; Teräsvirta and Anderson, 1992; Teräsvirta, 1994; McMillan, 2003). In this case, the full model is referred to as a logistic STR (LSTR) model.

$$F(y_{t-d}) = (1 + \exp(-\lambda(y_{t-d} - c)))^{-1}, \lambda > 0 \tag{12}$$

where $d$ is the delay parameter, $\lambda$ is the smoothing parameter, and $c$ is the transition parameter. This function is monotonically increasing in $y_{t-d}$. Note that when $\lambda \to +\infty$, $F(y_{t-d})$ becomes a Heaviside function: $F(y_{t-d}) = 0$ when $y_{t-d} \leqslant c$ and $F(y_{t-d}) = 1$ when $y_{t-d} > c$ .

However, monotonic transition might not always be successful in empirical applications. Therefore, the second form of transition

[8] These results are not presented here to save space but they are available upon request from the authors.

[9] We are thankful to an anonymous referee for making this suggestion.

[10] Table 6 includes the short-term (i.e. 3-month) real Treasury yield in $Z_t$. However, our results remain unaffected if we use the long-term (i.e. 10-year) Treasury yield or the term spread instead.

[11] We have also obtained results for longer horizons $h = 2, 3, 6$. Overall, we find that stock market volatility is a significant predictor of economic activity in Canada and in the US across all horizons and in the UK when $h = 2, 3$, while weak evidence is found in Japan. When $Z_t$ is incorporated in the model, our results reveal that the stock market volatility and the economic activity of the US are both significant predictors of the economic activity of the remaining countries when $h = 2, 3$. Overall, our findings suggest a strong degree of market integration and highlight the importance of the US regarding the economic activity of the considered countries.

**Table 6**
Linear forecasting regressions.

| Country | $Z_t = \emptyset$ | | $Z_t \neq \emptyset$ | | | | |
|---|---|---|---|---|---|---|---|
| | $SV_t$ | Adj. $R^2$ | $SV_t$ | $RTY_t$ | $SV_{US,t}$ | $BC_{US,t}$ | Adj. $R^2$ |
| Canada | −1.115*** | 0.159 | −0.095*** | 0.044*** | −1.740** | 0.420*** | 0.256 |
| | (3.12) | | (3.39) | (3.73) | (2.24) | (3.02) | |
| Japan | −3.140** | 0.037 | −1.950** | 0.014 | −7.920*** | 1.075*** | 0.165 |
| | (2.10) | | (2.14) | (0.90) | (5.00) | (3.58) | |
| UK | −0.480** | 0.041 | −0.380** | −0.003 | −0.059 | 0.543*** | 0.102 |
| | (2.37) | | (2.31) | (0.47) | (0.08) | (5.14) | |
| US | −2.157** | 0.360 | −2.159** | 0.023 | – | – | 0.362 |
| | (5.06) | | (5.06) | (0.56) | | | |

This table presents the results from the linear forecasting regressions described in Section 4.4.2 (Eq. (10)) during the full sample period (i.e. 1990:01–2011:12) and when the forecast horizon is 1. For each country, the dependent variable is the change in its economic activity (i.e. the log-change in the total industrial production index, which is our business cycle indicator, BC). The main predictive variable is the (first differenced) volatility of the corresponding country ($SV_t$) and $Z_t$ is a vector of other financial indicators that may contain useful information about economic activity such as the short-term real Treasury yield ($RTY_t$), the (first differenced) volatility of the US ($SV_{US,t}$) and the change in economic activity of the US ($BC_{US,t}$). For each regression, the estimated coefficients are given in the first row while the corresponding *t*-statistics are reported in parentheses below. Asterisks *** and ** denote significance at the 1%, and 5% levels, respectively.

function we consider is the exponential function with the relevant model in this case being referred to as an exponential STR (ESTR) model (see, Teräsvirta and Anderson, 1992; Teräsvirta, 1994; McMillan, 2003):

$$F(y_{t-d}) = 1 - \exp(-\lambda(y_{t-d} - c)^2), \lambda > 0 \quad (13)$$

In this case, the transition function is symmetric around *c*. The ESTR model implies that contraction and expansion have similar dynamic structures while the dynamics of the middle ground differ (Teräsvirta and Anderson, 1992). As there might be some issues in the STR models related to the estimation of the smoothing parameter $\lambda$ which can be problematic, we follow the literature and scale $\lambda$ by the standard deviation of the transition variable in the LSTR model and by the variance of the transition variable in the ESTR model (see, Teräsvirta and Anderson, 1992; Teräsvirta, 1994). Hence, we have the following versions of transition functions, respectively:

$$F(y_{t-d}) = (1 + \exp(-\lambda(y_{t-d} - c)/\sigma(y_{t-d})))^{-1}, \lambda > 0 \quad (14)$$

$$F(y_{t-d}) = 1 - \exp(-\lambda(y_{t-d} - c)^2/\sigma^2(y_{t-d})), \lambda > 0 \quad (15)$$

The results of the LSTR and the ESTR models are presented in Table 7.

Looking at the LSTR model results, we find that the estimated transition parameter *c*, which marks the half-way point between the two regimes, is significantly different from zero in Canada and in Japan (with the respective estimates being 0.17 and −0.09). Regarding the UK and the US, no such significance is found indicating that the lower and the upper regime in these markets represent, respectively, the two cases where the industrial production grows at a negative or a positive rate. Moreover, we observe that in all markets the lagged parameters of interest in the lower regime appear significant and their sign remains the same as in the linear case. In more detail, the estimated betas are negative and significant (at 1% and 5% levels, depending on the case) suggesting that high volatility predicts a lower industrial production growth rate in the following month. Additionally, the estimated $\gamma_1$'s show that the lagged stock market volatility of the US is a significant short-term predictor of the industrial production growth rate in Canada and Japan (at the 5% level) while the estimated $\gamma_2$'s suggest that the lagged industrial production growth rate of the US is significant in all cases. Based on the estimated $\varphi_1$, in the upper regime significance is found only in Canada revealing the importance of stock market volatility as an explanatory variable of industrial production growth rate in both regimes. Finally, the estimated parameter $\lambda$ indicates that the fastest speed of transition occurs in Canada, Japan and the US while the slowest occurs in the UK.

Turning to the estimated ESTR models, we observe a similar picture which establishes the importance of stock market volatility as a short-term predictor of future industrial production growth rate in a nonlinear context and corroborates the previously reported results

**Table 7**
Nonlinear forecasting regressions: STR models.

| Parameters | Canada | | Japan | | UK | | US | |
|---|---|---|---|---|---|---|---|---|
| | LSTR | ESTR | LSTR | ESTR | LSTR | ESTR | LSTR | ESTR |
| $\alpha$ | 0.001** | 14.180*** | −0.394** | 1.343* | −8.623** | −0.030* | −0.058*** | 1.340*** |
| $\beta$ | −0.020*** | −0.360*** | −0.032*** | −0.099** | −0.210** | −0.150** | −0.002** | −0.090*** |
| $\gamma_1$ (SVus,t) | −0.030** | −0.250*** | −0.003** | −0.007** | −0.010 | −0.030* | – | – |
| $\gamma_2$ (BCus,t) | 0.001** | 0.090*** | 0.001** | 0.003** | 0.004** | 0.090** | – | – |
| $\gamma_3$ (RTYt) | 0.016 | −9.200 | −0.055 | −0.236 | 0.410 | 0.330 | −0.427 | −0.230 |
| $\varphi_0$ | 0.0005 | −0.080 | 0.0004 | 0.104 | 0.860 | 0.030 | 0.100*** | −1.340 |
| $\varphi_1$ | −2.572* | −14.180** | 0.583 | 0.230* | −0.210 | 0.150 | 0.003 | 0.100 |
| $\varphi_2$ (SVus,t) | −0.031 | 9.210 | −0.091 | 0.004 | −0.090 | −0.002 | – | – |
| $\varphi_3$ (BCus,t) | −0.018 | 0.250 | 0.003 | 0.0011 | −0.110 | −0.012 | – | – |
| $\varphi_4$ (RTYt) | 0.020 | −0.360 | 0.048 | −0.007 | 0.940 | −0.330 | 0.754 | 0.230 |
| $\lambda$ | 5.340** | 5.360*** | 0.450** | 1.130* | 6.550 | 23.010 | 5.230*** | 1.130** |
| c | 0.170** | 0.960* | −0.093* | 0.387 | −0.650 | 0.001 | −0.008 | 0.380 |
| Adj.$R^2$ | 0.130 | 0.130 | 0.060 | 0.050 | 0.033 | 0.049 | 0.049 | 0.059 |

This table presents the results of the smooth-transition threshold (STR) models which were described in Section 4.4.2. LSTR refers to the case where the transition function is the logistic function while ESTR employs an exponential function instead. Results are reported for all markets under consideration during the full sample period (i.e. 1990:01–2011:12). Asterisks ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

under the linear scenario. Additionally, it also stresses the importance of the US stock market volatility and the US industrial production growth rate on the economic activity of other countries.

## 5. Conclusion

This paper empirically investigates the relationship between stock market volatility and the business cycle (represented by the industrial production growth rate) within an international setting which involves four major economies, namely the US, Canada, Japan and the UK. Our data set is at a monthly frequency and covers the period from 1990:01 to 2011:12. Although there is an abundance of evidence regarding the linkage between stock market volatility and the business cycle, there are still some important avenues of research which have not been explored. With respect to those, we contribute to the literature in the following ways.

First, we examine the dynamics between stock market volatility and the business cycle by employing both linear and nonlinear causality tests. The vast majority of previous studies focuses on the linear representation despite existing evidence which supports the nonlinear nature of various macroeconomic variables and of the relationship between them (e.g., Keynes, 1936; Hiemstra and Jones, 1994; Shiller, 1993, 2005; Diks and Panchenko, 2006; Shin et al., 2013). Second, we provide fresh evidence given that our sample includes the recent global financial crisis. In that respect, our data set is particularly advantageous as it allows us to assess the impact of the crisis which can be seen as a useful robustness check in a period of heightened volatility. Third, to our knowledge, this is the first study that conducts a multivariate analysis (both linear and nonlinear) in this context and assesses possible spillover effects under a cross-country framework. In particular, we extend the bivariate causality models and include the stock market volatility and the business cycle of the US to determine the impact on the corresponding variables of the remaining three countries. As in the bivariate case, the effect of the recent financial crisis is also considered in our multivariate analysis.

Our tests within a linear bivariate setting offer strong evidence of bidirectional causality between stock market volatility and the business cycle in all countries. The results are robust to the inclusion of the recent financial crisis and there are cases where the identified causal relationships strengthen during this period. Adopting a nonlinear framework also reveals a significant feedback (i.e. causality) in most cases suggesting that nonlinear features are present and important in capturing the dynamics between the considered variables. On the other hand, depending on the direction or country, there are instances where the crisis has led to the absence of nonlinear effects.

When we extend the bivariate analysis and adopt a linear multivariate framework, we identify significant spillover effects between the US stock market volatility and business cycle and the corresponding variables of the remaining three countries. These results are overall consistent throughout the financial crisis and some relationships are more pronounced during that period. In the case of Japan, this is a very interesting finding given that the bivariate tests showed somewhat weaker causality within this country. Moreover, when we explore multivariate causality within a nonlinear setting by employing a recently developed test by Bai et al. (2010), our results reveal the existence of significant nonlinear spillover effects across countries. This is more evident in the interaction between the UK and the US. However, the inclusion of the crisis leads to stronger nonlinear spillover effects among the US and Canada or Japan. This finding suggests that both a nonlinear approach and a cross-country framework may be able to capture the dynamics of the considered relationships to a greater extent during periods of heightened volatility.

Finally, we present evidence based on both linear and nonlinear forecasting regressions and show that the stock market volatility is a significant short-term predictor of future economic activity within each country. Additionally, we find that the stock market volatility and the economic activity of the US are also significant predictors of the economic activity of Canada, Japan and the UK indicating a strong degree of market integration.

Overall, the findings in this paper suggest that policies associated with a country's economic activity should take into consideration both the nonlinear features of the relationship between stock market volatility and the business cycle as well as potential spillover effects from other countries. This is particularly important in periods of heightened stock market volatility such as the recent global financial crisis.

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