US Economic Uncertainty, EU Business Cycles and the Global Financial Crisis[1]

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Abstract

This paper investigates the impact of the US economic uncertainty on the business cycles (changes in the industrial production) of twelve European Union (EU) countries before and during the global financial crisis. Empirical tests are conducted using the linear and nonlinear causality tests, impulse response function and variance decomposition. Results show ample evidence of causality from the US uncertainty to EU business cycles only when the crisis period is included in the analysis. Both the linear and non-linear tests confirm the significance of US uncertainty as a short-term predictor of business cycles of the EU.

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Business Cycles
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Uncertainty
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1. Introduction

Research interest in the economic uncertainty modelling and its role in predicting macroeconomic fluctuations have revived in the recent years (Caldara et al., 2016; Baker et al., 2015; Dzielinski, 2012; Jurado et al., 2015). During periods of financial crisis, economic uncertainty arises because of negative news, which lowers expectations of future economic activity. During the recent global financial crisis the US experienced an exceptional increase in macroeconomics and financial uncertainty (Cesa-Bianchi et al., 2014). Caldara et al., (2016) claim that the global financial crisis have cast doubt on the traditional sources of business cycles fluctuations.[2] And, in response recent research have pointed to economic uncertainty as alternative driver of economic fluctuation (Bloom, 2009; Bloom et al., 2014; Christiano et al., 2014; Gilchrist et al., 2014).

Lately, uncertainty has been defined in two different ways. First, according to Jurado et al. (2015) uncertainty is defined as the conditional volatility of a stochastic process that is not forecastable from the perspective of economic agents. Alternatively, Bloom (2009) and Baker et al. (2015) defined uncertainty as a situation where future state of the economy is not known with certainty.[3] They also report that the economic uncertainty is countercyclical i.e. uncertainty on average is much lesser in the expansionary times as compared to the recessions. This paper studies the effect of the global financial crisis on the spill-over effect of the US economic uncertainty on the European Union (EU) business cycles.

An increase in economic uncertainty can produce an adverse effect on the economy by reducing employment, investment and output through various channels (Bloom, 2009; Baker

[2] See Rebelo (2005) for a good discussion on the sources of business cycles fluctuations.

[3] This uncertainty can be triggered by various factors such as changes in the economic fundamentals and policies, heterogeneous future growth prospects and productivity movements, geopolitical scenarios and natural disasters, etc, (Baker et al., 2015).

et al., 2013; Colombo, 2013; Born and Pfeifer, 2014; Jurado et al., 2015). Some of the channels identified in the existing literature are i) real options effect (Bernanke, 1983); ii) precautionary savings effect (Leland, 1968), and iii) financial frictions effect (Gilchrist et al., 2014). On the demand side, higher uncertainty leads to reduction in investment demand for firms and delays in the new projects. This is because, the firms gather new information and are concerned due to irreversibility of costs involved. Households also respond to the uncertainty in a similar way, by reducing consumption of durable goods and waiting for certainty (Bernanke, 1983; Bloom, 2009; Bloom et al., 2014). On the supply side, in times of higher economic uncertainty, the employers curb the employment opportunities that reflect costly adjustment of personnel (Bloom, 2009; Bloom et al., 2014). The firms' ability to raise capital and finance their investment initiatives reduces significantly as the creditors tend to expect higher rate of returns. This leads to decline in the output growth rate. This negative correlation between macroeconomic uncertainty and the output is indicated by Claessens et al., (2012). Caldara et al., (2016) also indicate a robust negative effect of economic uncertainty on economic activity.

Research involving the US economic or economic policy uncertainty has predominantly focussed on the impact it has on the various US macroeconomic and financial variables. Many studies have highlighted that any significant shock that affects a leading economy, such as the US, is expected to result in a spill-over effect on to the macroeconomic variables as well as on to the financial markets of other countries (Favero and Giavazzi, 2008; Ehrmann and Fratzscher, 2009). However, evidence from literature on the spill-over effect of the US economic uncertainty shocks onto the economies of other countries is very limited. [4]

[4] Colombo (2013) finds a negative influence of the US uncertainty on macroeconomic variables of the total Euro area. In her research, though, Colombo does not apply individual EU countries' data. The 2013 IMF study shows that the policy uncertainty shocks in the US and the Euro area affected growth in other world regions. Klößner and Sekkel (2014) report that the uncertainty around the US and the UK economic policies has a greater impact on six other developed countries.

This paper addresses this gap in the literature by analysing the impact of the US economic uncertainty on the business cycles of the twelve European Union (EU) countries using the linear and nonlinear causality tests, impulse response function, and variance decomposition. We address the question: "Does the US economic uncertainty cause the economic activities of the major EU countries?" In this context, some important empirical questions arise: Is there is a causal relationship between US economic uncertainty and the business cycles of the EU countries which runs in either direction? Furthermore, is the nature of this relationship linear or are there nonlinearities that need to be taken into consideration? Even further, given the jump in the US uncertainty during the financial crisis period has this causality changed during the crisis period? This paper aims to provide empirical evidence on these unexplored avenues of research.

Thus, this paper intends to contribute to the existing literature in the following ways. First, we empirically investigate the causal relationship between US economic uncertainty and the business cycles (represented by the industrial production growth rate) of twelve major countries within the EU. Specifically, we employ monthly data from January 1991 to December 2015 from Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Spain and the UK. This potential causal relationship can be explained in terms of interdependence and integration between the US economy and the EU economy. According to Arora and Vamvakidis (2004) US is the growth engine of the world economy. They maintain that the most obvious channel in this regard is the trade linkage.[5] As changes in the US import demand directly reflects the variations in the net exports and

[5] Abbott et al. (2008) show that trade intensity and the business cycles corrections are positively related.

productivity in other countries[6]. Bagliano and Morana (2012) also find that trade is the key channel for real activity shocks. Similarly, U.S. foreign direct and portfolio investment play a large and growing role in world financial flows. These financial linkages also serve as source of transmitting shocks to other countries.

The volume of trade during 2012 between the US and the EU was around $1500 billion and accounted for one third of the global trade flows. According to the Transatlantic Economy (2014), the US and EU account for 56.7% of inward stock of FDI and 71% of outward stock of FDI. 15 million workers are employed in mutually on shored jobs on both sides of the Atlantic. US investment since 2000 in many European countries has up surged significantly, e.g. in comparison to China, 14 times more in the Netherlands, 10 times more in the UK and 6 times more in the Ireland. Give the direct link between the two economies it is of empirical interest to study the relationship between US economic uncertainty and EU business cycles. A significant spill-over from the US to EU will have major implications for the EU policy makers and economy.

Second, the vast majority of studies employ linear Granger causality tests (Granger, 1969) when assessing the relationship between various macroeconomics variables despite the fact that there is clear evidence which points out to the existence of nonlinearities (Shiller, 1993, 2005; Hiemstra and Jones, 1994; Shin et al., 2013). Thus, we also apply non-linear tests to investigate the causality between the variables. To the best our knowledge, no other study has applied nonlinear bivariate tests to assess the relationship between US economic uncertainty and EU business cycles.

[6] Grossman and Helpman (1989, 1990, 1991), Rivera-Batiz and Romer (1991a, 1991b), and Romer (1990) for a discussion of spillover effects from trade.

Third, we further study the potential effect of the global financial crisis on this causality. As stated earlier, there was a substantial increase in the US economic uncertainty during the global financial crisis. It is of empirical interest to see if the sudden jump in the US economic uncertainty imposed a substantial change in the spill-over from the US uncertainty to the EU business cycles. A substantial change in the spill-over will have significant policy and economic implications during the crisis era. Again, to the best of our knowledge, no other study empirically investigates the impact of the global financial crisis on the international spill over effect of the US economic uncertainty.

In this paper business cycles are measured as the monthly change in the industrial production of the twelve EU countries.[7] US economic uncertainty measures are adopted from Jurado et al. (2015). Following Jurado et al. (2015), uncertainty here is defined as *the conditional volatility of a disturbance that is unpredictable from the perspective of economic agents*.

Our results provide ample evidence of linear and nonlinear causality from the US uncertainty to the EU countries' business cycles when the crisis period is included in the analysis. During the pre-crisis period very little evidence of causality is found. Impulse response shows that innovations in the uncertainty trigger a significant change in the business cycles. Variance decomposition results further show that the US uncertainty shock explains a substantial share of variance of the forecast errors of the EU countries' business cycles. Finally, we employ both linear and nonlinear forecasting regressions and show that US economic uncertainty is an important short-term predictor of future economic activity within the EU countries. Overall, results indicate the need for EU policy makers to take into

[7] Bekaert et al. (2013) and Colombo (2013) also apply the changes in industrial production as the business cycles.

consideration both the US economic uncertainty spill-over effect and nonlinearities when assessing the EU economic outlook. This is especially true during, and after the global financial crisis.

The remainder of the paper is organised as follows. Section 2 describes the data and the methodological approach applied. Sections 3 and 4 provide a discussion of the empirical results. Finally, section 5 concludes.

2. Data Description and Methodology

2.1. The Data

As noted earlier we apply monthly data ranging from January 1991 to December 2015 from Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Spain and the UK. These countries represent the largest twelve economies from the EU.[8] Data regarding indices of industrial production for respective countries are obtained from Datastream. Figure 1 shows the growth rates in the industrial production indices of the major EU countries. The dip in the industrial production during the crisis period can be seen clearly in many cases, for example Finland, France, Italy, Spain and the UK. Uncertainty index data has been downloaded from Sydney Ludvigson's website[9]. Figure 2 presents the Jurado index of uncertainty (in levels) for the sample period. The sharp increase in uncertainty during the 2007-2008 global financial crisis is clearly visible. Figure 3 presents the changes in the Jurado index of uncertainty for the sample period. As noted earlier during the recent global financial crisis the US experienced an exceptional increase in macroeconomics and financial uncertainty (Cesa-Bianchi et al., 2014). Therefore, it is important to investigate the impact of the financial crisis in our study and provide some new

[8] Size of economies was based on real GDP in 2014 and 2015.

[9] Uncertainty index data have been downloaded from http://www.sydneyludvigson.com/data-and-appendices/

evidence. Empirical tests are first conducted for the pre-crisis period (January 1991 to June 2007) and then tests are conducted using the total sample period (January 1991 to December 2015) which includes the global financial crisis era.[10] In this manner, the effect of the crisis on the uncertainty spill-over may be investigated. We provide a through comparison of the results from the two sample periods.

As per standard practices, augmented DF test proposed by Dickey and Fuller (1979) and Kwiatkowski et al. (1992) KPSS tests show that the first difference series of the underlying variables are stationary during both periods, which are then employed for linear and nonlinear causality tests.[11] These results are not provided to save space but are available on request.

[Insert Figures 1 and 2 around here]

2.2. Economic Uncertainty

Although Economic Policy Uncertainty (EPU) by Baker et al. (2015) has recently gained popularity, its main drawback lies in its inability to reflect 'true uncertainty' because it fails to provide a rationale for the decision-making process by drawing extensively from economy-wide data. Jurado's index rather focuses on ameliorating these limitations by econometrically extracting the non-forecastable component of uncertainty and providing a measure which can be used directly in macroeconomic analysis, without suffering too much from possible endogeneity issues. Jurado's index is free from the structure of specific theoretical models, and from dependencies on any single observable economic indicator. The application of the nonlinear causality tests and the Jurado index to represent the economic uncertainty makes this paper unique in the literature.

[10] The start of the collapse of the US sub-prime mortgage market during July/August 2007 is applied as the start of the crisis period in this paper.

[11] We do not provide the description of the unit root tests as they are available at many sources.

Jurado et al. (2015) argue that the conventional econometric measures are not the true measure of uncertainty. In fact, Jurado et al. (2015) argue that 'the conditions under which common proxies are likely to be tightly linked to the typical theoretical notion of uncertainty may be quite special'.[12] In view of these limitations, Jurado's index exploit a data-rich environment to provide direct econometric estimates of time-varying US macroeconomic uncertainty.

In particular, Jurado's index define a $h-$period ahead of uncertainty in variable $y_{jt} \in Y_t = (y_{1t},, y_{N_y t})'$, and denote $\mathrm{U}_{jt}^{y}(h)$ to be the conditional volatility of the purely unforecastable component of the future value of the series;

$$U_{jt}^{y}(h) = \sqrt{E[\left(y_{jt+h} - E[y_{jt+h} \mid I_t]\right)^2 \mid I_t]}, \tag{1}$$

where $E(. \mid I_t)$ is taken with respect to information I_t available to agents at time t. An (objective) measure or index of macroeconomic uncertainty is then described as an aggregation of individual uncertainty at each date using aggregation weights w_j:

$$U_t^{y}(h) \equiv plim_{N_y \to \infty} \sum_{j=1}^{N_y} w_j U_{jt}^{y}(h). \tag{2}$$

The distinguishing feature of this measure of uncertainty from other aggregate measures is its ability to remove forecastable component[13] $E[y_{jt+h} \mid I_t]$ before computing conditional volatility. Failure to do so often leads to estimates that 'erroneously categorize forecastable variations as 'uncertain''. It is argued that Jurado's index measure of uncertainty provides superior econometric estimates of uncertainty that are as free as possible from the structure of

[12] For example, stock market volatility can change over time even if there is no change in uncertainty about economic fundamentals. Similarly, cross-sectional dispersion in individual stock returns can fluctuate without any change in uncertainty if there is heterogeneity in the loadings on common risk factors.

[13] From a large number of macroeconomic and financial variables.

specific theoretical models, and from dependency on any single (or small number) of observable economic indicators.

2.3. Linear Causality

Vector autoregression (VAR) specification is used in this paper to test the Granger causality (Granger, 1969) between changes in the business cycles (i.e. industrial production growth rate) and changes in the economic uncertainty index proposed by Jurado et al. (2015). This is aimed at assessing linear causal relationship between the variables in terms of time precedence. The VAR specification applied in this research are in the following form:

$$BC_t = \alpha + \sum_{i=1}^{n} \beta_i BC_{t-i} + \sum_{i=1}^{n} \gamma_i EcoU_{US,t-i} + \varepsilon_{1t} \quad (3)$$

$$EcoU_{us,t} = \theta + \sum_{i=1}^{n} \omega_i BC_{t-i} + \sum_{i=1}^{n} \varphi_i EcoU_{us,t-i} + \varepsilon_{2t} \quad (4)$$

In equations (3) and (4) BC and $EcoU_{us}$ denote the changes in the business cycle of selected European countries and the US economic uncertainty index, respectively. Equations 3 and 4 test bivariate causality between BC and $EcoU_{us}$. There is evidence of causality from US economic uncertainty ($EcoU_{us}$) to business cycles (BC) of the selected European countrieswhen γ_i are significant. Here presence of linear dependency would imply a possible spill over effect between the US economic uncertainty and the business cycles of the European countries. Dependencies can be unidirectional or bidirectional between variables which would imply feedback effect. In equation 4 significant ω_i indicates causality from the EU business cycles (BC) to the US uncertainty ($EcoU_{us}$). We only present results for equation 3. Equation 4 is estimated for each country and a summary of the result is provided in footnotes.

2.3. Nonlinear Causality

Nonlinearities in the macroeconomic time series have been reported by a large number of studies (Hiemstra and Jones, 1994; Shin et al., 2013, Shiller, 1993, 2005). Nonlinear causality was highlighted in the economics/finance literature by Hiemstra and Jones (1994) and subsequent research papers have provided further evidence in a nonlinear setting with respect to various economic/financial variables (Silvapulle and Choi, 1999; Chen and Wuh-Lin, 2004; Diks and Panchenko, 2006; Bekiros and Diks, 2008a, 2008b; Shin et al., 2013; and 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. 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, this research further aims at identifying the presence of nonlinear causality (spill-over effect) between the variables. Nonlinear causality is tested by means of the model proposed by Hiemstra and Jones (1994). This model is based on the correlation integrals, defined as the probability of the dynamic or lagged co-movement between the two stationary time series.

First, consider two strictly stationary and weakly dependent time series $\{X_t\}$ and $\{Y_t\}$, t = 1,2,….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,

$$
\begin{aligned}
& X_t^m \equiv (X_t, X_{t+1}, \ldots, X_{t+m-1}), \quad m = 1, 2 \ldots, \ t = 1, 2, \ldots, \\
& X_{t-Lx}^{Lx} \equiv (X_{t-Lx}, X_{t-Lx+1}, \ldots, X_{t-1}), \\
& \qquad\qquad Lx = 1, 2, \ldots, \ t = Lx + 1, Lx + 2, \ldots, \\
& Y_{t-Ly}^{Ly} \equiv (Y_{t-Ly}, Y_{t-Ly+1}, \ldots, Y_{t-1}), \\
& \qquad\qquad Ly = 1, 2, \ldots, \ t = Ly + 1, Ly + 2, \ldots,
\end{aligned} \tag{5}
$$

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

$$
\begin{aligned}
& Pr\left(\left\|X_t^m - X_s^m\right\| < e \,|\, \left\|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\right\| < e, \left\|Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly}\right\| < e\right) \\
& = Pr\left(\left\|X_t^m - X_s^m\right\| < e \,|\, \left\|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\right\| < e\right)
\end{aligned} \tag{6}
$$

In equation (6), Pr(·) denotes probability and ||·|| denotes the maximum norm. The left hand side of equation (6) 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 equation (6) 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 countries in our paper, X_t represent the business cycle represented by the industrial production growth rate for selected EU countries and Y_t is the US economic uncertainty index proposed by Jurado et al. (2015) represented by the industrial production growth rate for selected EU countries. Therefore, if equation (6) is true, this implies that the US economic uncertainty does not affect the respective business cycles of the EU countries i.e. no spillover effect.

To implement a test based on equation (6), Hiemstra and Jones (1994) express the conditional probabilities in terms of the corresponding ratios of joint probabilities:

$$\frac{C1(m+Lx,Ly,e)}{C2(Lx,Ly,e)}=\frac{C3(m+Lx,e)}{C4(Lx,e)} \tag{7}$$

where $C1$, $C2$, $C3$, $C4$ are the joint probabilities.[14] For given values of *m*, *Lx*, and $Ly \geq 1$ 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,

$$\sqrt{n}\left(\frac{C1\left(m+Lx,Ly,e,n\right)}{C2\left(Lx,Ly,e,n\right)}-\frac{C3\left(m+Lx,e,n\right)}{C4\left(Lx,e,n\right)}\right)\rightarrow N(0,\sigma^2(m,Lx,Ly,e)) \tag{8}$$

The appendix of Hiemstra and Jones (1994) provides further details regarding the definition and the estimator of the variance $\sigma^2(m,Lx,Ly,e)$. To ensure robustness, this model is capable of testing the bidirectional causality to avoid any bias caused by the feedback effect.

[Insert Table 1 around here]

3. Results

Table 1 presents linear causality results for both the sample periods. During the total sample including the crisis period (1991-2015) there is a significant evidence of linear spill-over effect of the US economic uncertainty to the business cycles of all twelve EU countries. . Using the pre-crisis sample (1991-2007) there is limited evidence of causality. Only in the cases of Austria and Germany business cycles there is significant causality from the US uncertainty. For both sample periods, respective lag orders for Granger causality have been

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

selected based on Aakiake and Hannan-Quin information criteria varying with maximum number of lags varying between 4 to 8 for different countries.

[Insert Table 2 around here]

Table 2 presents the nonlinear causality test results. These results are similar to the linear results. Using the total period there is significant evidence of nonlinear causality from the US uncertainty to the business cycles for nine out of the twelve EU countries. Only in the cases of France, Germany, and Greece do results fail to indicate any causality. The weak French and German results could be due to the strained ties between the US and these countries lately caused by the declining economies and resource crunch in these countries (Ahearn, 2008; Ahearn and Belkin, 2010). Once again during the pre-crisis period results only provide evidence of causality for Austria and Germany. This result is similar to the linear causality test. As expected there is clear evidence of increased causality from the US uncertainty to the EU business cycles when the crisis period is included in the analysis. This evidence is provided by both the linear and nonlinear tests.[15] The increase in both the causality when applying the crisis period is due to the increased economic uncertainty during the crisis period and increased economic linkage between the US and the EU.

[Insert Figures 4 and 5 around here]

[15] As note earlier, linear and nonlinear tests are also conducted to study the unidirectional causality the other way around that is the business cycles of the EU countries causing economic uncertainty in the US. These tests have been conducted for both pre and including financial crisis periods. Linear causality results show that the US economic uncertainty is not affected by most of the countries' business cycles except Germany and Netherlands where relatively weaker impact is observed at 10 percent significance level. In case of nonlinear tests, business cycles of the EU countries do not cause economic uncertainty in the US for both sample periods. These results are available on request from the authors.

Figures 4 and 5 presents the impulse response functions to a one-standard deviation shock to the uncertainty index for the pre-crisis and total samples, respectively. Impulse responses trace out the responsiveness of the dependent variables (business cycles) in the VAR to shocks to each of the variables (US uncertainty). The responses of business cycles of all countries are significant during both periods. During the total era including the crisis period (table 5) the responses of the Danish, French, Irish, Italian, Spanish and the UK business cycles suggest an immediate decline in production; for example, the lowest value for the French business cycle is reached after five months at more than -8%. Then these slowly return to their pre-shock level after a period of more than one year. The Italian and the UK results are also very similar to the French result, while the Spanish business cycle takes almost twenty months to reach the pre-shock level. The lowest value for the Irish business cycle is less than -4% after five months, but the pre-shock level is reached relatively quickly after eight months. The Danish result is similar to the Irish result but with much smaller change. For the remaining countries the initial reaction is a jump in the business cycles and then a decline afterwards; for example, in Finland, after a 2% jump within two months, there is a decline to -3% after four months. The climb to the pre-shock level is reached after twelve months. The Greek result is similar to the Finnish result, while results from Austria, Belgium, Germany and Netherlands are very similar. After an initial jump, the lowest level is reached after four months but within seven months recovery is observed and the climb to the pre-shock level takes more than eighteen months. A comparison with the pre-crisis results (figure 4) shows a less responsiveness of the business cycles to the one-standard deviation to the US uncertainty. The average time for the business cycles to return to the pre-shock level is faster during the pre-crisis period. This is especially true in the cases of Belgium, Germany, Greece, Ireland, Italy, Netherlands, Spain and the UK. Impulse response results confirm and back the results of the causality tests that adding the crisis years to the analysis clearly shows the increase in the impact and importance of the US economic uncertainty on the business cycles of the EU countries. [16]

4. Robustness Check

This section builds upon the causality results reported above and aims to empirically test the role of the US economic uncertainty as a short-term predictor of the changes in the business cycles of the twelve European countries. This section compliments and strengthens the evidence of Granger linear and nonlinear causality as well as a significant robustness check. These tests are only conducted for the total period. For this purpose, initially focus on the linear forecasting regression:

$$y_{t+h} = a + \beta x_t + \sum_{i=0}^{\gamma} \gamma_i y_{t-i} + \epsilon_{t+h} \qquad (9)$$

Where y_{t+h} refers to the changes in the business cycles (i.e. the industrial production growth), $y_{t+h} = \frac{1200}{h+1} ln\left(\frac{Y_{t+h}}{Y_t}\right)$, h>0 is the forecast horizon, and x represents the changes in the US economic uncertainty. The null hypothesis of β =0 is tested here to observe the predictability of changes in the business cycle using the US economic uncertainty. The corresponding results for h=1 are presented in table 3.

[Insert Table 3 around here]

We report that the US economic uncertainty is a significant short-term predictor of the business cycle of most of the EU countries in sample, with the exception of Denmark, Greece

[16] Further investigation is conducted by means of the variance decomposition of the forecast errors. The variance decomposition highlights the contribution of the US uncertainty in explaining the short-run fluctuations in the EU business cycles Using the total period, at six months, the US uncertainty shocks explains more than 5% of the variation in the business cycles of Austria, France, Italy, Spain and the UK. At twelve months and later, and only in the cases of Denmark, Greece, and Ireland, the US uncertainty shock explains less than 5% of the variation. US economic uncertainty in the pre-crisis period explains relative lesser variation in the business cycles of the EU countries as compared to the full sample period. At six months, less than 1% variation in the business cycle of all the selected EU countries may be attributed to the US uncertainty shocks. These results are available on request from the authors.

and Ireland. These forecasting results reaffirm and strengthen the evidence of spill over effect of the US economic uncertainty on the major EU countries.

We further extend the forecasting approach presented above and report evidence based on nonlinear forecasting models, which allows us to further enhance our understanding of the underlying relationship between the US economic uncertainty and EU countries' business cycles. In this context, smooth-transition threshold (STR) models are employed for nonlinear forecasting (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 limit abrupt change in parameter values, STR models allow for smooth variations between different regimes. The threshold model is presented as follows:

$$y_{t+h} = \alpha + \beta x_t + \sum_{i=0}^{p} \gamma_i y_{t-i} + \left(\varphi_0 + \varphi_1 x_t + \sum_{i=0}^{p} \theta_i y_{t-i} \right) F(y_{t-d}) + \varepsilon_{t+h} \tag{10}$$

where all variables are defined as in equation (9) 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 equation (11) (see also, Chang 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.

$$F(y_{t-d}) = (1 + \exp(-\lambda(y_{t-d} - c)))^{-1},\ \lambda > 0 \tag{11}$$

where$d$ is the delay parameter, λ 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 $y_{t-d} \le c$ 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 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):

$$F(y_{t-d}) = 1 - \exp(-\lambda(y_{t-d} - c)^2),\ \lambda > 0 \tag{12}$$

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 λ which can be problematic, we follow the literature and scale λ 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:

$$F(y_{t-d}) = (1 + \exp(-\lambda(y_{t-d} - c) / \sigma(y_{t-d})))^{-1},\ \lambda > 0 \tag{13}$$

$$F(y_{t-d}) = 1 - \exp(-\lambda(y_{t-d} - c)^2 / \sigma^2(y_{t-d})),\ \lambda > 0 \tag{14}$$

Table 4 presents the results of the LSTR and the ESTR models. In the LSTR model results, the estimated transition parameter *c*, which marks the half-way point between the two regimes, is significantly different from zero in most of the EU countries, except for Denmark, France, Greece and Ireland. Moreover, we observe that in most of the estimated betas are negative and significant (at 1% and 5% levels, depending on the case) suggesting that high US economic uncertainty forecasts a lower industrial production growth rate in the following month. Further the estimates of φ_1,in the upper regime significance is found in six out of ten EU countries revealing the importance of US economic uncertainty as an explanatory variable of industrial production growth rate in both regimes for these countries. Insignificant results are found for Denmark, France, Greece and Ireland. Finally, the estimated parameter λ indicates that the fastest speed of transition occurs in Finland, while the slowest are observed in Austria, Germany, Netherlands and the UK. Once again the speed coefficient is insignificant for the same four countries.

Results for the estimated ESTR models are very similar to the LSTR results. This reaffirms the significance of the US economic uncertainty as a short-term predictor of future changes in the business cycles of the EU countries in a nonlinear context and compliments the previously reported results under the linear framework. These results reinforce the idea that the US is often seen as "the engine" of the world economy (Dees and Saint-Guilhem, 2011), any sign of slowdown or rise in the uncertainty raises concerns about adverse spill over effects to other economies.

5. Conclusion

An increase in economic uncertainty can affect an economy by reducing employment, investment and output. During periods of financial crisis, uncertainty arises because of negative news, which lowers expectations of future economic activity. Any significant shock that affects a leading economy, such as the US can potentially have a spill-over effect on the macroeconomics variables and financial markets of other countries. This potential causal relationship can be explained in terms of interdependence and integration between the US economy and the EU economy. However, empirical evidence on this spill-over effect of the US economic uncertainty shocks on the economies of the other countries is very limited and the evidence on the effect of the financial crisis on this spill-over is non-existent. This paper attempts to fill these gaps in the literature. This paper studies the impact of the US economic uncertainty during pre-crisis and crisis periods on the business cycles of twelve major EU countries using the linear and nonlinear causality, impulse response function and variance decomposition. We apply monthly data ranging from January 1991 to December 2015 from Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the

Netherlands, Spain and the UK. Tests are first conducted for the pre-crisis period (January 1991 to June 2007) and then for the total sample which includes the crisis period. In this manner, the impact of the financial crisis on the spill-over effect of the US uncertainty on EU business cycles may be investigated. Business cycles are measured as the monthly changes in the industrial production and US economic uncertainty are adopted from Jurado et al. (2015). Uncertainty here is defined as the conditional volatility of a disturbance that is unpredictable from the perspective of economic agents. Jurado's index exploit a data-rich environment to provide direct econometric estimates of time-varying US macroeconomic uncertainty.

Results provide ample evidence of linear and nonlinear causality from the US economic uncertainty to the EU business cycles when the crisis period is included in the study. . There is very little evidence of causality during the pre-crisis period. Only in the cases of Austria and Germany there is evidence of causality. This result clearly indicates the increase in the importance of the US economic uncertainty during the crisis period. This result has implications for EU policy makers and businesses. Impulse response shows that innovations in the uncertainty trigger significant changes in the business cycles. These significant changes are more prominent when the crisis period is included in the sample. Variance decomposition results show that the US uncertainty shocks explains a decent share of variance of the forecast errors of the EU countries' business cycles. For robustness check, we test the role of the US economic uncertainty as a short term predictor of the changes in the business cycles. For this purpose, we apply both the linear and non-linear forecasting methods. Both tests indicate that US uncertainty is a significant short term predictor of the business cycles of most of the EU countries.

Overall, the findings in this paper suggest that policies associated with EU countries economic activity should take into consideration the spill-over effect of the US economic uncertainty and the nonlinear features of the relationship between the business cycles and the US uncertainty. This is particularly important in periods of heightened economic uncertainty such as the recent global financial crisis.

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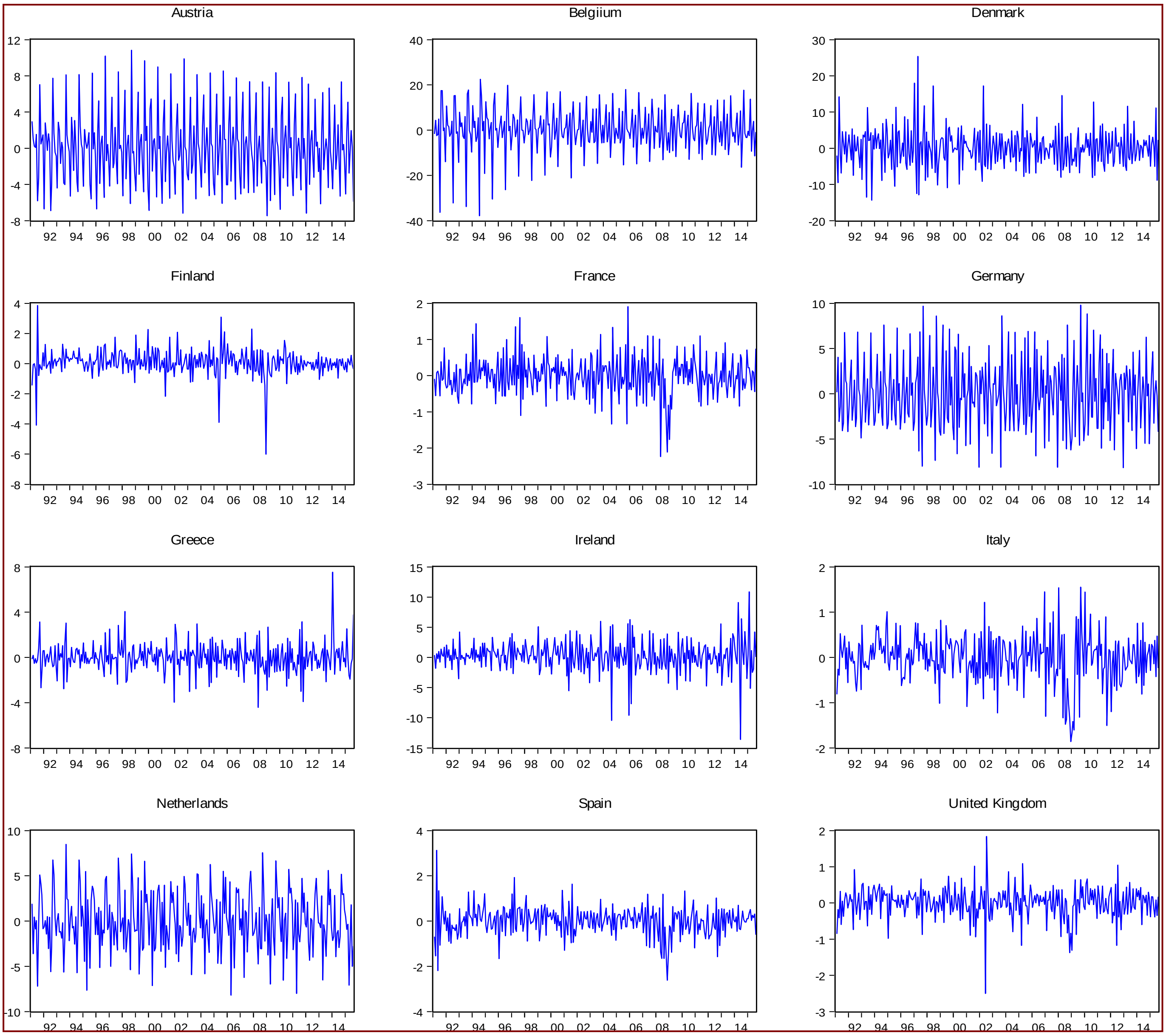

Figure 1: Industrial Production Growth Rates

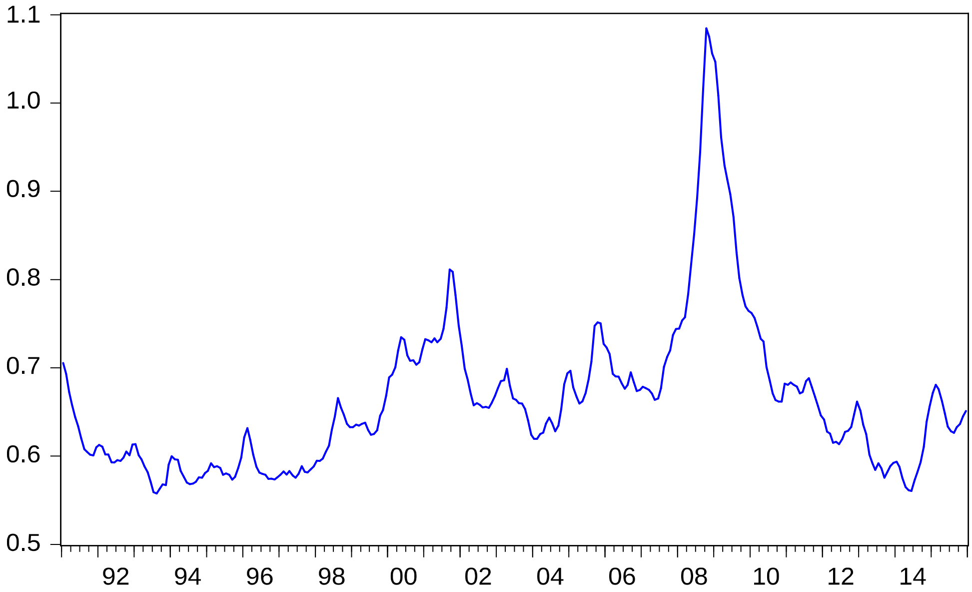

Figure 2: US Economic Uncertainty in levels

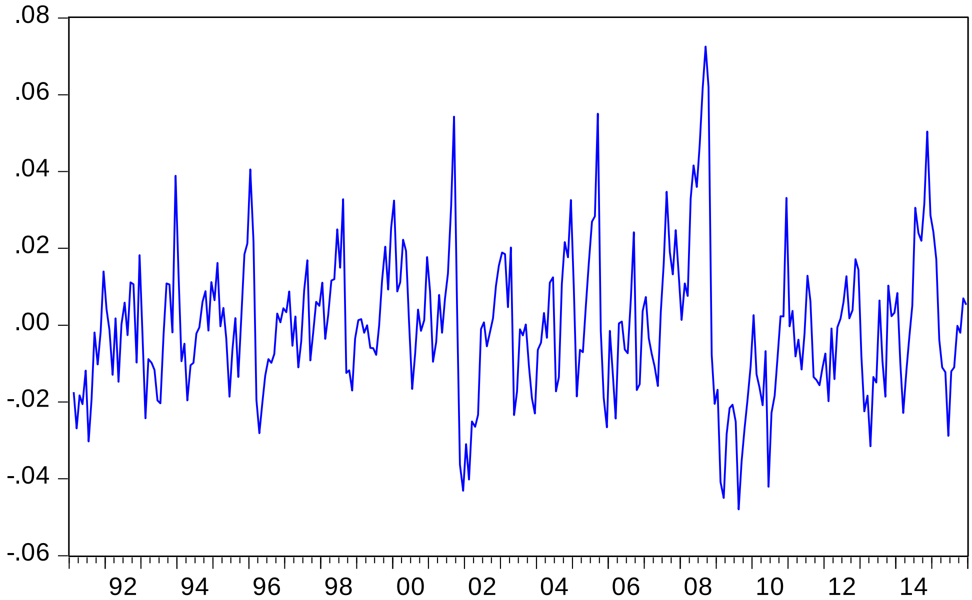

Figure 3: First Difference of US Economic Uncertainty

Table 1 Linear Causality Results

Countries	US Eco. Uncertainty → BC	
	Before Financial Crisis	**After Financial Crisis**
Austria	25.95***	29.24***
Belgium	10.2	27.46***
Denmark	7.69	11.51*
Finland	4.66	22.54**
France	6.76	34.92***
Germany	14.76**	34.95***
Greece	4.56	20.13**
Ireland	4.46	22.71**
Italy	3.51	30.34***
Netherlands	8.98	18.11***
Spain	8.47	28.66***
United Kingdom	6.09	27.12***

Notes:

Table 1 presents the results of the bivariate linear causality tests, described in Section 3.1, between the US economic uncertainty index proposed by Jurado et al. (2015) and the business cycle (represented by the industrial production growth rate) for selected European countries. Results are shown with respect to the pre-crisis and full sample periods to assess the impact of the recent financial crisis. Asterisks ***, ** and * denote significance at the 1%, 5% and 10% conventional levels respectively. Standard diagnostic tests such as Ramsey's Specification Test (RESET), White's Heteroskedasticity Test; LB: Ljung-Box (1978) test for autocorrelation up to 12 lags; and Jarque-Bera normality of residuals test have been applied.

Table 2
Nonlinear Causality Results from Uncertainty to Business Cycles

Countries	**US Eco. Uncertainty → BC**	
	Before Financial Crisis	**After Financial Crisis**
Austria	1.85**	1.50*
Belgium	0.89	5.80***
Denmark	0.55	2.01**
Finland	0.65	1.930**
France	0.75	0.27
Germany	2.99***	0.024
Greece	1.01	1.37
Ireland	1.07	1.73**
Italy	0.91	1.81**
The Netherlands	0.73	2.17**
Spain	0.97	2.49***
United Kingdom	1.05	2.34***

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 the US economic uncertainty index proposed by Jurado et al. (2015) and the business cycle (represented by the industrial production growth rate) for selected European countries. Results are shown with respect to the pre-crisis and full sample periods to assess the impact of the recent financial crisis. Asterisks ***, ** and * denote significance at the 1%, 5% and 10% conventional levels respectively.

Figure 4 : Impulse Response Functions – Before Financial Crisis

(Response of BC to Cholesky One S.D. Innovations in US Eco Uncertainty)

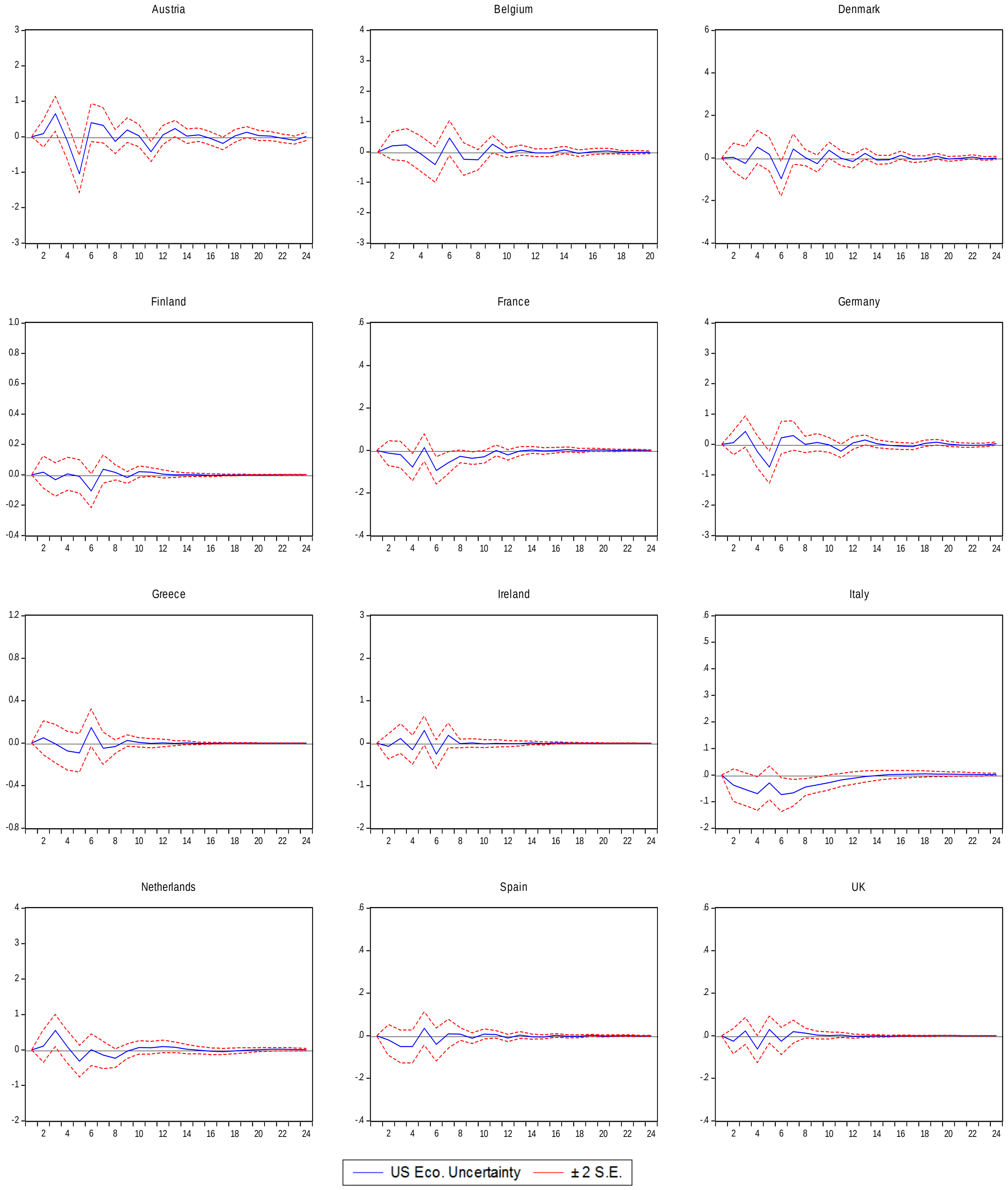

Figure 5: Impulse Response Functions – Total Period
(Response of BC to Cholesky One S.D. Innovations in US Eco Uncertainty)

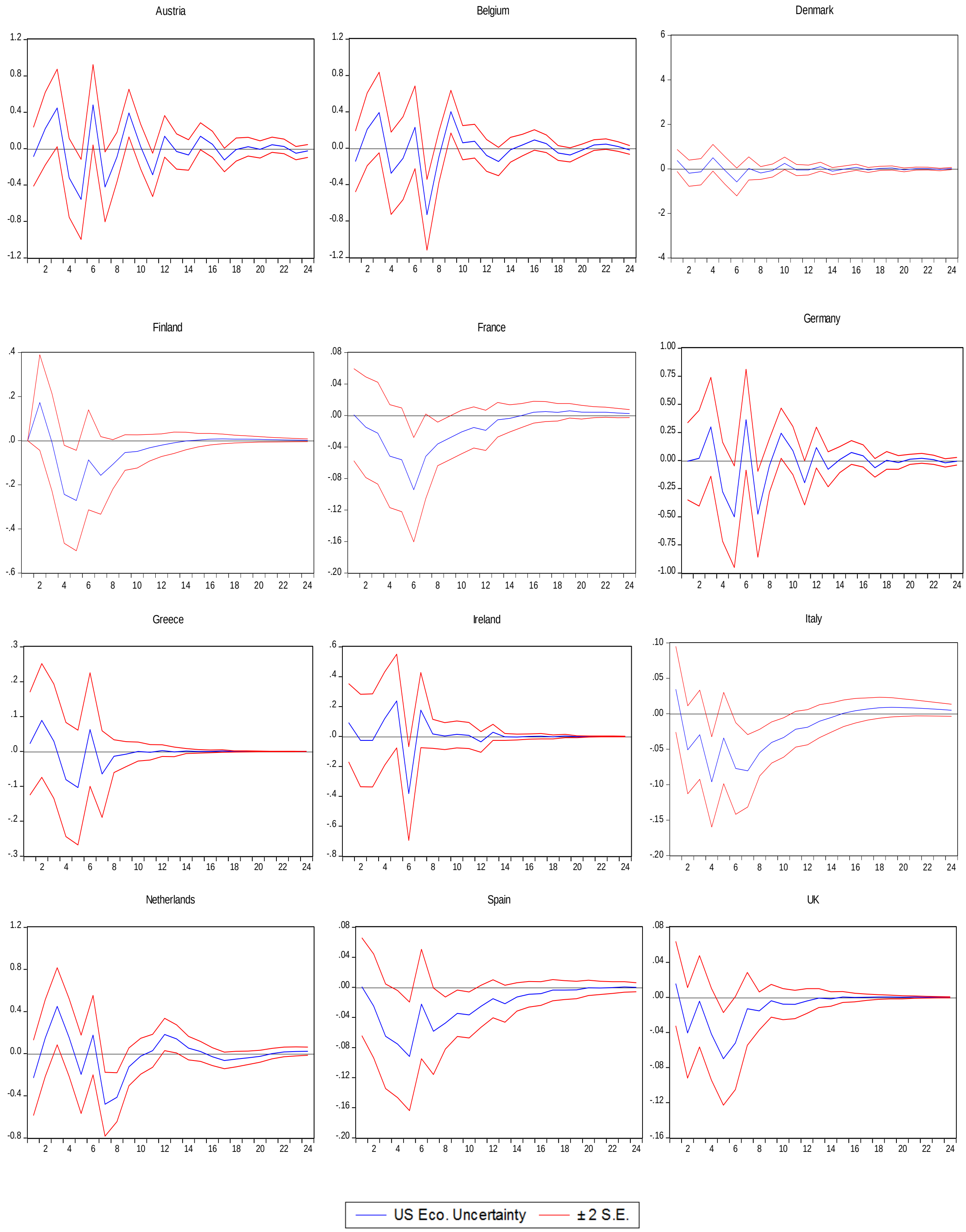

Table 3: Linear Forecasting Results

Country	JEU	Adj. R^2
Austria	6.49** (2.23)	0.52
Belgium	5.94** (2.03)	0.48
Denmark	1.50 (0.79)	0.42
Finland	-0.43* (1.92)	0.056
France	-1.019** (1.97)	0.164
Germany	-1.88** (2.41)	0.41
Greece	0.479 (0.37)	0.12
Ireland	1.89 (0.82)	0.26
Italy	-1.57** (2.95)	0.14
Netherlands	4.15** (2.44)	0.27
Spain	-1.96*** (3.46)	0.19
United Kingdom	-1.25*** (3.03)	0.13

This table presents the results from the linear forecasting regressions described in Section 5 (equation (9)) during the full sample period (i.e. Jan-1991 to Dec-2015) 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 change in the US economic uncertainty index proposed by Jurado et al. (2015). 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.

Table 4: Nonlinear Forecasting Results

Panel – I: Exponential Smooth Transition Threshold Model (ESTR)

Country	α	ß	φ_0	φ_1	λ	c	Adj. R^2
Austria	-52.04***	10.49***	56.99***	-5.33***	0.055**	-17.29***	0.69
Belgium	19.80**	-1.14**	-79.13***	17.64***	1.18	19.49***	0.64
Denmark	38.60	-41.15	-27.57	41.56	0.0016	-15.93	0.38
Finland	13.31***	-19.69***	-11.49***	18.83***	9.71***	-19.71***	0.27
France	-4.63	-3.51*	5.09	2.45	0.089	-9.28***	0.25
Germany	-51.21**	-8.6**	57.34**	8.26*	0.046**	-49.28	0.54
Greece	-0.04	-0.99	11.45	0.05	0.006	44.63	0.14
Ireland	11.93	-5.09	-3.75	11.73	4.70	-6.74	0.22
Italy	-40.84	-55.72***	40.72***	55.54***	0.10***	-60.74**	0.28
Netherlands	-7.31	5.30**	-25.71**	-5.41**	0.035**	13.06**	0.53
Spain	22.55	-16.37**	-22.22	15.14**	0.144**	-20.34	0.23
UK	-5.67	-4.21***	6.52	3.77**	0.068**	-7.30**	0.18

Panel – II: Logistic Smooth Transition Threshold Model (LSTR)

Country	α	ß	φ_0	φ_1	λ	c	Adj. R^2
Austria	-7.67**	2.04***	12.03*	2.24**	0.091**	2.38**	0.74
Belgium	31.27***	11.97**	-25.35***	-16.52	0.012***	23.52***	0.69
Denmark	23.82	29.45	23.71	28.01	0.568	-3.775	0.37
Finland	1.96***	0.42***	-11.5***	-6.07***	0.03***	3.73***	0.19
France	0.84	-0.46	-2.19	-2.67	0.049	15.47***	0.24
Germany	3.33**	-4.53**	0.37	6.93*	0.048**	1.94**	0.44
Greece	3.36	-5.46	-2.79	5.14	0.013	-1.009	0.12
Ireland	-14.74	-33.8	14.81	35.08	0.063	19.05**	0.31
Italy	5.66	2.75**	-6.02	-5.14**	0.064**	1.66***	0.20
Netherlands	-17.56***	5.01**	16.97*	-4.27**	0.015***	-42.33***	0.52
Spain	0.56	-2.17**	-1.61	-6.43***	0.003*	-1.61**	0.26
UK	1.02**	-1.53**	-1.22	0.31***	0.013***	39.89**	0.19

This table presents the results of the smooth-transition threshold (STR) models which were described in Section 5. 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 countries under consideration during the full sample period (i.e. Jan-1991 to Dec-2015). Asterisks ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.