# If the Unites States sneezes, does the world need "pain-killers"?

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**Abstract**

In this paper we analyze the extent to which the US economy affects international business fluctuations across countries and we ask whether the nonlinear nature of the business cycle affects the degree of co-movement between countries. A multivariate nonlinear LSTAR model is estimated for the GDP cyclical components of China, France, Germany, the UK and the US. This nonlinear framework allows the asymmetries of the business cycle to be captured properly to identify the synchronization behavior across countries. Our re-

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sults suggest that there is a relevant influence of the US cycle, specifically during recessions.

**JEL classification:** C32, E32, F15.

**Keywords:** Business Cycle, nonlinearities, synchronization, decoupling.

# 1 Introduction

In the last few decades, developed economies such as US, the EU members countries and to some extent Japan have intensified trade and financial linkages.[1] This fact, along with other forms of economic integration,[2] has raised the question of whether business cycles are synchronized. Frankel and Rose (1998), Stock and Watson (2005), Baxter and Kouparitsas (2005), Calderon et al. (2007) and Inklaar et al (2008), among others,[3] have found that greater trade integration stimulates the spillover of aggregate demand shocks, thereby increasing the co-movement of outputs. In contrast to these findings, Doyle and Faust (2002, 2005), Kose, Prasad and Terrones (2003) and Heathcote and Perri (2004) have found little evidence of a tendency toward an increasing international synchronization of cyclical fluctuations. Instead, cyclical convergence is observed among the major countries in the Euro-zone (Helbling and Bayoumi, 2003; Del Negro and Otrok, 2003; Luginbuhl and Koopman, 2004) and possibly between Canada, the US and the UK (Helbling and Bayoumi, 2003).

Theoretically, the link between trade integration and the synchronization of business

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[1]According to the U.S. Department of Commerce, exports from the US to the EU increased from 143.9 billion US dollars in 1997 to 271.8 billion US dollars in 2008. Imports from the EU to the US showed a similar increasing pace: 160.9 and 367.6 billion US dollars in 1997 and in 2008, respectively. As of 2008, US exports to the EU accounted for 21% of total US exports, whereas US imports from the EU accounted for 17.5% of total US imports. The trade relationships with Japan have also been intensified during the same period but to a lesser extent: exports from the US to Japan increased by 12.7%, whereas US imports from Japan increased by 14.5%. On the other hand, between 1998 and 2008, EU direct investment in the US increased by 185%, whereas US direct investment in the EU increased by 195%. In the case of the increase of direct investment in Japan, the rates are 74% and 81% from the EU and the US, respectively.

[2]The empirical literature has suggested that other factors may also affect business cycle synchronization, such as monetary integration (Fatás, 1997), fiscal policy (Clark and van Wincoop, 2001) or the exchange rate regime (Bordo and Helbling, 2003).

[3]For a survey on the determinants of the business cycle, see De Haan et al. (2008)

cycles remains ambiguous. Backus et al. (1992) show in a two-country open-economy model with complete financial markets that in a world of fully integrated asset markets, high trade intensity is associated with lower business cycle correlation. Krugman (1993) and Kose and Yi (2002) argued that more trade may encourage the increased specialization of production, thus causing less synchronization of the business cycle. However, according to Imbs (2004), not only the volume of trade but also the similarity of production structures makes an impact. Imbs (2004) and Shin and Wang (2004) conclude that industry-specific shocks can cause more business cycle synchronization when bilateral trade concentrates on intra-industry trade rather than on inter-industry trade. Canova and Dellas (1993) developed a theoretical model to show that the spread of technology shocks through trade can also make business cycles more correlated across countries.

In addition, the link between financial integration and output co-movement is not unambiguous. According to Imbs (2004), if capital flows are correlated internationally, closer financial integration leads to greater output synchronization. In a model in which individuals have incomplete access to international risk-sharing instruments, Baxter and Crucini (1995) show that output fluctuations are positively correlated. However, the ability to borrow and lend internationally facilitates the transfer of resources between economies, and this ability can decrease output correlations. Backus et al. (1992) show that in a complete-markets model, a positive technological shock in one economy attracts capital flows from the rest of the world, resulting in negatively correlated output fluctuations. Kalemli-Ozcan et al. (2001) claim that better income insurance attained through greater capital market integration may lead to greater specialization of production and, hence, output fluctuations that are less symmetric.

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Empirical evidence of the link between financial integration and business cycle co-movement is often contradictory. Kalemli-Ozcan et al. (2001) and Heathcote and Perri (2004) conclude that higher financial integration leads to a decline in the correlation of output; however, Imbs (2004, 2006) finds more synchronization within countries with strong financial links. Additionally, Kim et al (2007) show that shocks to capital flows generate positive business cycle correlations.

To the extent that business cycles can be interpreted as an economy's response to shocks, an assessment of the degree of business cycle synchronization is of paramount importance to understand the international transmission of country-specific as well as global shocks. A high degree of output co-movement will limit the ability of an economy to weather a US slowdown or a global recession, decreasing the scope of counter-cyclical policies in mitigating the impact of external shocks. On the other hand, idiosyncratic shocks can be potentially smoothed through the stabilizing effects of international trade and financial risk sharing. An assessment of the degree of business cycle synchronization is also important in the context of increasing coordination of macroeconomic policies among countries. If a common source of shocks explains a large portion of the variance of the growth rates of individual economies, policy coordination should not be costly. This principle is embedded in the optimal currency area theory in the sense that the more synchronized business cycles are, the smaller the cost of giving up an independent monetary policy.

In this paper, we analyze the link between business cycle synchronization and the asymmetric nature of business cycles. The latter refers to the fact that the dynamics

of recessions are different from those of expansions.[4] Our primary question is: does the nonlinear nature of business cycles affect the degree of co-movement between countries? If nonlinearities cannot be neglected, the estimates of co-movement from a linear model would be inaccurate.

To answer this question, we investigate the nature of macroeconomic interdependence between the US, Japan, China and the three largest European economies (France, Germany and the UK). The inclusion of France and Germany, the largest economies in the Euro zone, will help to verify if the response of these countries to external shocks is different. An asymmetric transmission of shocks would challenge the implementation of the common monetary policy. The UK is the largest economy in the non-Euro area of the EU. If the UK economy is more strongly linked to the US business cycle than the economies of France or Germany are, it might not be advisable for the UK to strengthen its macroeconomic policy coordination with Euro countries. Japan is included in this analysis as a control country. Japan has endured slow economic growth and recessions during the past two decades, while US economic growth has been stronger. Because these two countries have experienced two different economic trajectories, a strong link between both business cycles should not be observed. In addition, the relative significance of Japan and the US as economic partners has diminished in favor of China and other emerging economic powers. The inclusion of China is a further test of this decoupling hypothesis.

This paper contributes to the debate on business cycle synchronization by building

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[4]Early studies on business cycle asymmetry can be traced back to Mitchell (1927), Keynes (1936) and Burns and Mitchell (1946), who noted that contractions in an economy are quicker and steeper but also shorter-lived than expansions; therefore, economic activity follows an asymmetric cyclical process. This nonlinear nature of the business cycle has been documented by Neftci (1984) and Sichel (1989), among others

a multivariate nonlinear model to increase our knowledge of what generates business cycles across countries. First, we identify a common channel of international propagation through a common feature analysis. The presence of common cycles shows the importance of common transmission mechanisms in generating international business cycles. Second, we estimate a nonlinear system of business cycles under the restriction of a common cycle. As demonstrated by Centoni et al (2006), imposing the common cycle restriction to the estimated model helps to more accurately estimate the responses to shocks because redundant parameters are excluded. Third, we perform stochastic dynamic simulation to measure the dynamic adjustment of each country in response to changes in the common cycle. Finally, we use quarterly GDP rather than annual or monthly data, which have been used in previous papers. According to Shermman and Kolk (1997), the best data to use in cycle analysis are quarterly data. Output series measurements evaluate the movements of the overall economic activity better than do labor productivity or the industrial production index. Our modeling approach allows us to answer questions such as: Do international outputs co-move because of the existence of common dynamics? Which countries are less synchronized? How different are the adjustment dynamics of national business cycles across countries in response to positive and negative innovations in the common cycle?

Asymmetries in business cycles have implications for both theory and policy. If non-linearities of business cycles are not negligible, the effects of expansionary and contractionary monetary policy shocks on output are not symmetric (Narayan and Popp, 2009). In addition, any nonlinearities would invalidate measures of the persistence of monetary policy and other shocks on output that are based on linear models, including those derived

from vector autoregressions. If foreign demand shocks are largely responsible for output fluctuations, there is room for Keynesian-type policies to smooth the effect of foreign disturbances. In contrast, if cycles are the optimal response to unforeseen disturbances of both domestic and foreign origin, as postulated in the real business cycle literature, the best the government can do is to reduce uncertainties. If nonlinearities are present, theories of business cycles cannot be validated merely by matching the first and second moments of data with the moments implied by the theories in question.

Our results suggest that the international transmission of shocks is asymmetric, meaning that negative shocks are transmitted in a far more intense manner than positive shocks are. This result highlights the importance of nonlinearities in accounting for business cycle co-movements and gives empirical support to our assumption that more US recessions contribute to more co-movement among countries. Our results also show important differences among countries. The UK is clearly the country that is most severely affected by the changes in the US business cycle, whereas China is situated at the opposite end of the scale, as it is only very moderately affected by the US business cycle. Finally, our estimated transition function accurately reproduces each of the periods in which the US economy went into a recession. The fact that our model captures these important episodes highlights the importance of nonlinear models over linear models in terms of their ability to explain business cycle co-movements as well as the robustness of our estimated model.

Our results have important implications for policymakers. If fluctuations in economic activity are driven by a common cause, policy institutions should then focus on the identification of markets and channels that foster cross-country transmission to properly react to these changes. National policies aiming at national cycles are less important.

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This is the case in the UK, which required a generous dose of "painkillers" to mitigate the effects of US downturns. China represents the opposite case. Our results also provide useful insights regarding macroeconomic policy coordination within Europe. Given that the UK is strongly influenced by the US business cycle, the former should not strengthen its macroeconomic policy coordination with Euro countries. In addition, the fact that two Euro countries, Germany and France, react differently to the US business cycle makes the implementation of the common euro monetary policy more difficult. Finally, given the importance of asymmetries and the nonlinear dynamic of business cycles, the reliance on linear models in policy analysis may overlook important features of the data.

The structure of the paper is as follows. Section 2 describes the data and presents an overview of the business cycle in the countries under consideration. Section 3 explains the methodology. Section 4 reports the results, and conclusions are drawn in Section 5.

## 2 Data and stylized facts

Business cycle synchronization between China, France, Germany, Japan, the US and the UK is analyzed using quarterly real GDP, covering the period between the first quarter of 1978 and the fourth quarter of 2008. As a data source, we use the IMF's International Financial Statistics. Data for China's GDP was taken from the National Bureau of Statistics of China. Cycles are obtained as the first seasonal difference of the log of the real GDP. The estimated cycles are plotted in Figure 1, where the dashed areas represent the US economic recession according to the NBER.

The use of growth cycles to measure business cycles is not free from criticism. First,

the resulting cycles are noisier than the corresponding deviation cycles obtained with ad hoc filters such as the Hodrick-Prescott filter. Second, as indicated by Baxter and King (1999), first-differencing removes a trend from a series but potentially at the cost of a shift in the peaks and troughs of the differenced series as well as a great deal of volatility. However, this phase shift may not be too important when comparing cycles across countries, as we do in this paper, because the shift is the same for both countries. On the other hand, filtering is not free from criticism either. As noted by Benati (2001), if an economy is characterized by stochastic trends, economic fluctuations in business cycle frequencies will also contain fluctuations in those stochastic trends, and therefore, the estimated cycles will be contaminated with changes in the underlying stochastic trend. This identification problem is absent when differencing. In addition, filters such as the Hodrick-Prescott, Baxter-King and Christiano-Fitzgerald filters have recently been criticized by Gordon (2010) owing to the fact that these filters might introduce spurious dynamics in the filtered data.[5] Because we aim to assess the existence of common transmission dynamics between cycles in this paper, the use of filters is not advisable because of the risk of inducing spurious cycles. In conclusion, our measure of the cycle is obtained as the first seasonal difference of the log of the real GDP.

From Figure 1, one feature becomes very apparent: the observed co-movement among the business cycles of the developed countries increased during the periods of US recessions, and specifically during the last three recessions. In the 1980s, the business cycles appeared to be detached from each other regardless of the US recessions. However, in early 1990s, the cycles clearly co-moved in the face of the US slowdown. Synchronization

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[5]This idea is not new, however; see, for example, the study by Cogley and Nason (1995).

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among developed countries lasted up to mid-1990s. The recession in the 2000s repeated the pattern observed in the 1990s with a lower degree of co-movement. During the current crisis, co-movement among countries has dramatically increased, including countries with emerging economies, such as China. It seems that the deeper the US recession, the greater is degree of synchronization that is observed.

Next, we present some primary evidence of causality between business cycles. The use of Granger causality tests will provide a preliminary idea of which cycle(s) can be useful in forecasting the remaining cycles.

Table 1 presents a simple causality test between the analyzed business cycles.[6] Granger causality tests are often sensitive to the number of lags used. Here, the reported results are from a test using 4 and 8 lags, that is, at least 1 year long, because domestic factors tend to dominate business cycles in periods shorter than 1 year. Thus, the transmission effect of external shocks may be offset by spurious common domestic factors. The test results suggest that movements in the US business cycle provide useful information to predict movements in the cycles of China, France, Germany and the UK at 1- and 2-year lags, whereas they only "Granger-cause" the Japanese business cycle at a 2-year lag. In addition, the German business cycle is also useful in predicting the French and the UK business cycles at 1- and 2-year lags. These results highlight the fact that Germany may play an important role in the transmission of international shocks across European countries; however, the US exerts the largest global influence.

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[6]Only the results of causality tests from the US and Germany are shown. For the rest of the countries, the test results are available upon request.

# 3   Methodology

The possible nonlinearity of business cycles has a long tradition in economics. As noted by Teräsvirta and Anderson (1992), the issue of the nonlinearity of business cycles is important because it has clear implications on business cycle theory. Three parametric time-series models have been proposed to capture steep, short recessions. The first model, proposed by Hamilton (1989), divides the business cycle into two phases, negative trend growth and positive trend growth, with the economy switching back and forth between these phases according to a latent variable. The second model econometrically formalizes the theoretical model by Friedman (1963, 1964), who suggested that recessions are periods in which output is hit by large negative transitory shocks, labeled "plucks" by Friedman (see Kim and Nelson, 1999). The third model corresponds to the threshold autoregressive (TAR) model proposed by Tong (1978). The idea of the TAR model is to approximate a general nonlinear autoregressive structure by a threshold autoregression with a small number of regimes. Granger and Teräsvirta (1993) generalized the TAR model to the smooth transition autoregressive (STAR) model. In this framework, the business cycle indicator alternates between two distinct regimes which represent two phases of the business cycle. The transition between regimes is smooth, so STAR models can therefore be interpreted as a continuum of states between extreme regimes.

In this paper, we apply the STAR methodology to model business cycle synchronization. This approach is especially suitable in this context for several reasons. First, it considers the existence of different states of the world or regimes, allowing for the possibility that the dynamic behavior of economic variables depends on the regime that

exists at any given point in time. We believe that this constitutes a natural approach to modeling time-series models with nonlinear models. Second, these models are quite general and highly flexible, so they can quite satisfactorily approximate a wide variety of actual nonlinearities encountered in observed time series. Third, this regime-switching approach assumes that the regime can be characterized by an observable variable so that the regimes that have occurred in the past and present are known with certainty. In our case, this variable is of paramount importance because we aim to assess the degree of business cycle synchronization subject to the existence of an observed common cycle. Fourth, Teräsvirta (1994) proposes a technique for the specification and estimation of STAR models that is relative easy to implement and facilitates the economic interpretation of the results.

The STAR model can be formulated as

$$y_t = (\alpha + \sum_{i=1}^{p} \phi_i y_{t-i})(1 - F(\gamma, x_{t-d} - c)) + (\tilde{\alpha} + \sum_{i=1}^{p} \tilde{\phi}_i y_{t-i})F(\gamma, x_{t-d} - c) + \varepsilon_t, \quad (1)$$

where $\alpha$, $\tilde{\alpha}$, $\phi_i$, $\tilde{\phi}_i$, $\gamma$ and $c$ are the parameters to be estimated, and $\varepsilon_t$ is an i.i.d. error term with zero mean and constant variance $\sigma^2$. The transition function $F(\gamma, x_{t-d} - c)$ is continuous, non-decreasing and bounded between 0 and 1. The exogenous variable $x_{t-d}$ is the so-called transition variable and determines the regimes of the endogenous variable.

The STAR model specification in (1) allows for two extreme regimes associated with the values $F(\gamma, x_{t-d} - c) = 0$ and $F(\gamma, x_{t-d} - c) = 1$, each corresponding to a specific state of the economy. [7] When $x_{t-d}$ deviates from the constant threshold value $c$, there is

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[7]Thus, the STAR model can be interpreted as a continuum of regimes wihtin the two extreme regimes

a transition between regimes whose speed is governed by the parameter $\gamma$.

Two popular choices of transition functions are the first-order logistic function:

$$\text{LSTAR: } F(\gamma, x_{t-d} - c) = (1 + exp\{-\gamma(x_{t-d} - c)\})^{-1}, \;\; \gamma > 0, \tag{2}$$

and the exponential function:

$$\text{ESTAR: } F(\gamma, x_{t-d} - c) = 1 - exp\{-\gamma(x_{t-d} - c)^2\}, \;\; \gamma > 0. \tag{3}$$

The first one delivers the logistic STAR (LSTAR) model and encompasses two possibilities depending upon the transition speed $\gamma$. When $\gamma \to \infty$, the logistic function approaches a constant and the LSTAR model becomes a two-regime threshold autoregressive TAR model, for which changes between regimes are sudden rather than smooth. When $\gamma = 0$, the LSTAR model reduces to a linear AR model. Due its different responses to positive and negative deviations of $x_{t-d}$ from $c$, the LSTAR specification is convenient for modeling asymmetric behavior in time series. This is not the case of the exponential STAR (ESTAR) specification, in which these deviations have the same effect, i.e. what matters is the size of the shock, not the sign. Consequently, this model is only able to capture nonlinear symmetric adjustments.

Following Granger's (1993) "specific-to-general" strategy for building nonlinear time series models, Granger and Teräsvirta (1993) and Teräsvirta (1994) developed a technique for specifying and estimating parametric STAR models. This procedure can be summarized in four steps (van Dijk *et al.*, 2002): (i) Specification of a linear AR model of

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order $p$ for the time series under investigation; (ii) Test of the null hypothesis of linearity against the alternative of STAR; (iii) Selection of the appropriate transition function for the transition variable, if linearity is rejected; (iv) Model estimation.

Testing linearity against STAR is a complex matter because, under the null hypothesis of linearity, the parameters in the STAR model are not identified. Granger and Teräsvirta (1993) suggested a sequence of tests to evaluate the null hypothesis of an AR model against the alternative of a STAR model. These tests are conducted by estimating the following auxiliary regression for a chosen set of values of the delay parameter $d$, with $1 < d < p$:[8]

$$y_t = \beta_0 + \sum_{i=1}^{p} \beta_{1i} y_{t-i} + \sum_{i=1}^{p} \beta_{2i} y_{t-i} x_{t-d} + \sum_{i=1}^{p} \beta_{3i} y_{t-i} x_{t-d}^2 + \sum_{i=1}^{p} \beta_{4i} y_{t-i} x_{t-d}^3 + \epsilon_t. \qquad (4)$$

The null hypothesis of linearity against a STAR model corresponds to: $H_0 : \beta_{2i} = \beta_{3i} = \beta_{4i} = 0$ for $i = 1, 2, ..., p$. The corresponding LM test has an asymptotic $\chi^2$ distribution with $3(p+1)$ degrees of freedom under the null hypothesis of linearity. If linearity is rejected for more than one value of $d$, the value of $d$ corresponding to the lowest $p$-value of the joint test is chosen. In small samples, it is advisable to use $F$-versions of the LM test statistics because these F-versions have better size properties than the $\chi^2$ variants (the latter may be heavily oversized in small samples). Under the null hypothesis, the $F$ version of the test is approximately $F$ distributed with $3(p+1)$ and $T - 4(p+1)$ degrees of freedom.

If linearity is rejected, we need to test for LSTAR against ESTAR nonlinearity. For

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[8]Equation (4) is obtained by replacing the transition function in the STAR model (1) by a suitable Taylor series approximation (see Granger and Teräsvirta, 1993).

this purpose, Granger and Teräsvirta (1993) and Teräsvirta (1994) proposed the following sequence of tests within the auxiliary regression (4):

$H_{03} : \beta_{4i} = 0 \ \ i = 1, 2, ..., p$

$H_{02} : \beta_{3i} = 0 | \beta_{4i} = 0 \ \ i = 1, 2, ..., p$

$H_{01} : \beta_{2i} = 0 | \beta_{3i} = \beta_{4i} = 0 \ \ i = 1, 2, ..., p.$

An ESTAR model is chosen if $H_{02}$ has the smallest p-value, otherwise the selected model is the LSTAR.

If business cycles are inherently nonlinear, the analysis of the possible cyclical co-movement between countries requires the use of multivariate nonlinear methods. However, the complexity of multivariate nonlinear modeling leads us to test whether economic reasoning and data allow us to simplify this modeling. One possible simplification stems from the presence of common nonlinear components. Let us assume that within a given set of variables, there is a nonlinear behavior of each individual variable with respect to the same transition variable. If this is the case, we can test whether there is nonlinear co-movement within this set of variables. To address this issue, we test for common LSTAR nonlinearities following the methodology proposed by Anderson and Vahid (1998) based upon canonical correlations. Accordingly, let

$$y_t = \pi_{A0} + \pi_A(L)y_t + F(z_t)[\pi_{B0} + \pi_B(L)y_t] + \epsilon_t$$

be the multivariate version of the LSTAR model, where $y_t$ is the vector of variables under analysis, $\pi_i(L)$ is a matrix polynomial of degree $p$ in the lag operator, $\epsilon_t$ is i.i.d., and $F(z_t)$ is a diagonal matrix containing the transition functions for each series. Testing for

common nonlinearities consists in testing whether some $\alpha$ exists such that $\alpha' y_t$ does not exhibit the type of nonlinearity which is present in the mean of each individual $y_t$. The test statistic is based on canonical correlations and is asymptotically distributed as $\chi^2$ with $(3p-1)5s+s^2$ degrees of freedom, where $p$ denotes the maximum lag length and $s$ is the number of common nonlinearities. Rejection of the null hypothesis provides evidence of the presence of at most $s$ common nonlinearities.

# 4 Empirical results

In this section, we first analyze whether the business cycles of China, France, Germany, Japan, the US and the UK present nonlinearities and whether such nonlinearities are linked to the behavior of the US business cycle. Next, we carry out a common feature analysis to test for the existence of common dynamics (or cycles) among the analyzed countries. The existence of common cycles will provide us with information regarding the degree of synchronization among the analyzed countries. Having shown the existence of common nonlinearities, we estimate a multivariate STAR model under the constraint of the existence of common features and report dynamic stochastic simulations.

## 4.1 Analysis of nonlinearities

Before proceeding with the estimation of the STAR models, it is necessary to test for the null hypothesis of linearity. If linearity is not rejected for a country, we can exclude it from model-building efforts. Table 2 displays the test statistics for the null hypothesis of linearity against STAR nonlinearity. The results appear under the heading *"Linearity*

*Test"*. These tests are performed for each variable using the GDP of the US growth rate as the transition variable, i.e., $x_t$ in equations (1) and (4). The linearity tests were also estimated by using the business cycles of the countries other than the US as the transition variable. In the case of the US cycle, however, the rejection of linearity was far clearer. According to the results, linearity is rejected for all variables using the Granger and Teräsvirta (1993) linearity test with the only exception of Japan, which must be excluded from the rest of the analysis. This result has a twofold implication. First, except for Japan's business cycle, the business cycles exhibit a nonlinear behavior, and second, the transition between both regimes is at least partially driven by the cyclical component of the GDP of the US.

In contrast to the evidence of nonlinear behavior, Koop and Potter (2001) suggest that apparent nonlinearities in macro data could be due to instabilities, not to true nonlinearities. To explore whether our findings of nonlinearities could be driven by instabilities, we apply the Bai and Perron (2003) approach to detect multiple structural breaks in the linear models. The results are shown in Table 3, which reports the $SupF_T(k)$ statistics tests for the null hypothesis of no structural breaks against k breaks, and the sequence of $SupF_T(l+1|l)$ statistics tests for $l$ versus $l+1$ breaks. Following Bai and Perron (2003), the number of breaks can be determined by either using those F-tests, or by using and information criteria. LWZ in Table 3 corresponds to the modified Schwarz criterion by Liu et al (1997). According to the results, the data do not support a break model for any country with the only exception of China. For tChina, the LWZ and $SupF_T(l+1|l)$ suggest one break, whereas the BIC and $SupF_T(k)$ conclude in favor of two breaks.

To further investigate the presence of structural breaks, we re-estimate the Bai and

Perron (2003) test by using $Dusa_{t-1}$ as the threshold variable to test for instabilities. Thus, we replace the time trend as the threshold used in Table 3 with the transition variable selected according to the linearity tests. The results are similar to those in Table 3. In the case of China, however, only one break is not rejected in contrast to the two breakpoints found using the time trend as a threshold variable. The breakpoint is located in 1984:1 with a confidence interval of [1983:4, 1984:2] at the usual 5% significance level.[9]

Overall, the evidence of structural breaks does not support the idea that nonlinearities are caused by structural breaks. Furthermore, in the case of China, the only case in which we found such instabilities, the break is too close to the beginning of the sample, which may not cause misspecification in the nonlinear tests.

Once the existence of nonlinearities has been established and we have checked that these nonlinearities are not caused by neglected instabilities, we can proceed to test whether the adjustment to the changes in the transition variable are either symmetric or asymmetric. As previously indicated, if the transition function is exponential, the implied adjustment will be symmetric, whereas if the transition function is logistic, the adjustment will be asymmetric. Table 2 presents the Granger and Teräsvirta (1993) tests for choosing between the ESTAR and the LSTAR models (under the headings $H_{01}$, $H_{02}$ and $H_{03}$). According to these test statistics, the LSTAR representation of the data is preferred to the ESTAR representation, i.e., $H_{02}$ does not present the smallest $p$-value, for all GDP growth rates. Thus, all cyclical components of the GDPs respond asymmetrically to the cyclical component of the GDP of the US.

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[9]The structural break detected in 1984 in China can be explained by the reform of the non-state sector, which is crucial to understanding the rapid growth of this country since that time.

## 4.2   Analysis of common nonlinearities

Having shown that each of the business cycles of China, France, Germany, the US and the UK present nonlinearities and that these nonlinearities are linked to the behavior of the US business cycle, it becomes possible to determine in a multivariate context whether this nonlinear component is common to all the countries analyzed. One useful methodology for such purposes is the procedure for testing for common nonlinear components proposed by Anderson and Vahid (1998). Table 5 presents the results for the common LSTAR nonlinearities test proposed by these authors. These results are obtained using the cyclical component of the GDP of the US as the (common) transition variable. Using the standard procedure with 5% as the critical value, the null hypothesis that there are no nonlinear factors in the system is rejected, whereas the null hypothesis that there is only one such factor is not rejected. These tests, therefore, provide evidence that the nonlinear behavior of the cyclical component of GDP for the analyzed countries[10] shares a common nonlinearity that is identified with the cyclical component of the GDP of the US, which therefore acts as a common driving force.

## 4.3   Estimation of the multivariate STAR model

Once the existence of a nonlinear common component has been identified, a multivariate nonlinear system can be estimated for the set of cycles analyzed under the constraint of the existence of this nonlinear common component. Estimating an economic system with common components offers two clear advantages. First, it allows for greater parsi-

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[10]Japan has been excluded from this analysis because the linearity test fails to reject the null hypothesis on the linearity of the Japanese cycle with respect the US cycle.

mony, which is especially important in the case of nonlinear multivariate systems, and second, knowledge about these common components can also help to understand the economic linkages between variables. Table 6 presents the estimated nonlinear system where, according to the result from the common nonlinear test, the transition variable in the transition function is the first lag of the US business cycle.

The common LSTAR transition function appears at the bottom of Table 6, and Figure 2 plots this function (on the vertical axis) against the lagged value of the US business cycle. There seems to be a reasonable number of observations above and below the equilibrium, so we can be reasonably confident about our selection of the LSTAR specification. It is clear, however, that the observations are rather clustered in the upper regime, that is, when $F(\gamma, x_{t-d})=1$, so that the dynamics are governed by the sum of the coefficients of both AR branches in (1), that is, $(\phi_i + \tilde{\phi}_i)$. The dominant roots of the upper regimes are locally stable (i.e., the modules of the unit root are below one), with the only exception of China, which presents a unit root in the upper regime. This result might reflect the persistent and high growth of the Chinese economy during the last twenty years.

Figure 3 presents the transition function over time. The dashed areas represent the US economic recession according to the NBER. It is easy to see that the upper regime, $F(\gamma, x_{t-d})=1$, corresponds to periods of economic expansion, whereas the lower regime, $F(\gamma, x_{t-d})=0$, corresponds to periods of economic recession. Even more importantly, the estimated transition function accurately reproduces each of the periods in which the US economy went into a recession. The fact that our model adequately captures these important episodes highlights the importance of the nonlinear models over the linear models in terms of explaining business cycle co-movements as well as the robustness of

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our estimated model.

Although the business cycles of the countries analyzed show co-movement, this finding does not mean that all of the countries in the sample react to fluctuations in the US business cycle in the same way. To evaluate the extent to which each country reacts to the US cycle, dynamic stochastic simulations must be performed. The standard tool for measuring dynamic adjustment in response to shocks is the impulse response function. The properties of impulse response functions for linear models do not hold for nonlinear models. In particular, the impulse response function of a linear model is invariant with respect to the initial conditions and to future innovations. With nonlinear models, in contrast, the shape of the impulse response function is not independent with respect to the history of the system at the time the shock occurs, the size of the shock considered or the future path of the exogenous innovations (Koop, Pesaran and Potter, 1996). In this paper, we calculate the impulse response functions with a Monte Carlo simulation.

Figure 4 plots the impulse response function for a positive and negative shock of one standard deviation of the US business cycle in the transition function. All responses are statistically significant. There is a clear asymmetric response to positive and negative shocks. The negative shocks are transmitted to the other economies in a far more intense manner than the positive shocks. This result highlights the importance of nonlinearities in accounting for business cycle co-movements and gives empirical support to our assumption that a higher frequency of US recessions contributes to greater co-movement among countries. Given that linear models may put too little weight on sharp movements during recessions, a linear specification will underestimate the degree of business cycle synchronization.

To gain further insight not just on the statistical but on the economic relevance of the nonlinearities, we carry out a simple exercise where we estimate the share of covariance between countries explained by GDP nonlinearities. For this purpose we calculate the difference in the estimated covariances between our nonlinear model and the best-fitting linear alternative. The results are clear for the case of France, Germany and the UK, where covariance increases 17.3%, 21.5% and 20.7% respectively. In contrast, in the case of China the estimated increase in covariance is only 3.7%, and therefore, GDP nonlinearities account only for a small increase in the estimated co-movement with the US business cycle.

The impulse response functions also show important differences between countries. The UK is clearly the country that is most severely affected by the changes in the US business cycle, whereas China is situated at the opposite end of the scale because it is only very moderately affected by the US business cycle.

Our results are important both for academics and policymakers. From an academic point of view, we have shown that the presence of common cycles facilitates the study of similarities in economic fluctuations. In addition, given the importance of nonlinearities, theories of business cycles cannot be validated merely by matching the first and second moments of data with the moments implied by the theories in question. From a policy point of view, if fluctuations in the economic activity of countries with different institutions, economic structures and policies are driven by a common cause, international markets play a significant role in understanding business cycles. Policy institutions should then focus on the identification of markets or channels that foster cross-country transmission. This is the case in the UK, which is the country in the sample that appears to

be the most synchronized with the US. UK policymakers are required to carefully monitor international conditions and to disentangle the informational content in US cyclical disturbances to properly react to these changes. The opposite can be said of China. Our analysis suggests that China is rather decoupled from the US, meaning that policymakers in China can focus on national policies rather than on counter-cyclical policies to mitigate the impact of external shocks. Our results also provide useful insights regarding macroeconomic policy coordination within Europe. Given that the UK is strongly influenced by the US business cycle, the former should not strengthen its macroeconomic policy coordination with Euro countries. In addition, the fact that France reacts in a more intense manner in comparison to Germany implies that the US business cycles could potentially cause asymmetric effects in these two Euro countries. This fact can make the implementation of the common Euro monetary policy more difficult. Finally, given the importance of asymmetries and the nonlinear dynamics of business cycles, reliance on linear models in policy analysis may exclude important features of the data.

# 5 Conclusions

In recent years, there has been a considerable amount of debate over the extent to which shocks in the US economy are transmitted to other countries. Increased trade and financial integration, among other forms of economic integration, may have acted as mechanisms of transmission of the fluctuations of the US business cycle. A slowdown in US growth is often the precursor to turning points in economic activity that might spill over into other countries.

In this paper, we analyze the extent to which the US economy affects international business fluctuations and whether this cycle constitutes a common channel of international propagation. Give the nonlinear nature of business cycles, we adopt a nonlinear multivariate framework to properly capture business cycle asymmetries to identify the synchronization behavior across countries. Our primary question is: does the nonlinear nature of business cycles affect the degree of co-movement between countries? If nonlinearities cannot be neglected, the estimates of co-movement from a linear model would be inaccurate. A multivariate nonlinear LSTAR model is estimated for the cyclical components of the growth in the GDPs of China, Germany, France, the UK and the US. Our results suggest that the cycle of each of the countries shows nonlinearities and that these nonlinearities are linked to the behavior of the US business cycle, which acts as a nonlinear common component. The presence of common cycles highlights the role of common transmission mechanisms in generating international business cycles.

To observe the extent to which each country reacts in response to changes in the common cycle, dynamic stochastic simulations must be performed. The impulse response functions show a clear asymmetry before positive and negative shocks. These results emphasize the importance of nonlinearities in accounting for business cycle co-movements. There are also important differences between countries: while the UK clearly responds to shocks in the US business cycle, thereby displaying an obvious cyclical synchronicity, China's response to the US business cycle is far more modest.

Finally, the estimated transition function accurately reproduces each of the periods in which the US economy went into a recession. The fact that our model adequately captures these important episodes highlights the importance of the nonlinear models

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over the linear models in terms of their ability to explain business cycle co-movements as well as the robustness of our estimated model.

Our results have important implications for policymakers. If fluctuations in economic activity are driven by a common cause, policy institutions should then focus on the identification of markets and channels that foster cross-country transmission to properly react to these changes. National policies aiming at national cycles are less important. This is the case in the UK, which required a generous dose of "painkillers" to mitigate the effects of US downturns. China is the opposite case. Our results also provide useful insights regarding macroeconomic policy coordination within Europe. Given than the UK is strongly influenced by the US business cycle, the former should not strengthen its macroeconomic policy coordination with Euro countries. Additionally, the fact that two Euro countries, Germany and France, react differently to the US business cycle makes the implementation of the common Euro monetary policy more difficult. Finally, given the importance of asymmetries and the nonlinear dynamic of business cycles, reliance on linear models in policy analysis may overlook important features of the data.

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Table 1: Granger linear causality test

**US does not Granger-cause:**

| Lags | China | France | Germany | Japan | UK |
|------|-------|--------|---------|-------|------|
| 4 | **0.089** | **0.001** | **0.076** | 0.217 | **0.003** |
| 8 | **0.075** | **0.005** | **0.040** | **0.048** | **0.005** |

**Germany does not Granger-cause:**

| Lags | China | France | Japan | UK | US |
|------|-------|--------|-------|------|-------|
| 4 | 0.727 | **0.081** | 0.797 | **0.013** | 0.699 |
| 8 | 0.214 | **0.058** | 0.670 | **0.100** | 0.539 |

Notes: P-values for the F test are reported. Figure in bold implies rejection of the null hypothesis of absence of causality at the 10% significance level.

Table 2: Linearity test

|  | Linearity Test | $H_{01}$ | $H_{02}$ | $H_{03}$ |
|---|---|---|---|---|
| China | 0.000 | 0.061 | 0.506 | 0.000 |
| France | 0.000 | 0.000 | 0.019 | 0.262 |
| Germany | 0.002 | 0.005 | 0.611 | 0.156 |
| Japan | 0.208 | 0.107 | 0.743 | 0.174 |
| US | 0.000 | 0.488 | 0.342 | 0.000 |
| UK | 0.000 | 0.003 | 0.198 | 0.000 |

Note: p-values are shown. Transition variable US. Prob. is the p-value associated to the null hypothesis of linearity.

Table 3: Bai Perron (2003) test for multiple breaks

Threshold variable: time trend

**US**

| Breaks | RSS | BIC | LWZ | $SupF_T(k)$ | $SupF_T(l+1|l)$ |
|--------|-----|-----|-----|-------------|------------------|
| 0 | 0.0074 | -9.17* | -8.80* | - | - |
| 1 | 0.0051 | -9.11 | -8.36 | 3.96 | 3.96 |
| 2 | 0.0040 | -8.93 | -7.79 | 3.37 | 2.23 |

**China**

| Breaks | RSS | BIC | LWZ | $SupF_T(k)$ | $SupF_T(l+1|l)$ |
|--------|-----|-----|-----|-------------|------------------|
| 0 | 0.0001 | -13.16 | -12.83 | - | - |
| 1 | 0.0000 | -14.73 | -14.06* | 62.24(R) | 62.24(R) |
| 2 | 0.0000 | -14.76* | -13.74 | 44.73(R) | 4.73 |

**France**

| Breaks | RSS | BIC | LWZ | $SupF_T(k)$ | $SupF_T(l+1|l)$ |
|--------|-----|-----|-----|-------------|------------------|
| 0 | 0.0125 | -8.71 | -8.38* | - | - |
| 1 | 0.0082 | -8.75* | -8.08 | 5.42 | 5.42 |
| 2 | 0.0058 | -8.70 | -7.68 | 5.26 | 3.69 |

**Germany**

| Breaks | RSS | BIC | LWZ | $SupF_T(k)$ | $SupF_T(l+1|l)$ |
|--------|-----|-----|-----|-------------|------------------|
| 0 | 0.0208 | -8.20* | -7.87* | - | - |
| 1 | 0.0178 | -7.97 | -7.30 | 1.76 | 1.76 |
| 2 | 0.0143 | -7.81 | -6.79 | 2.10 | 2.22 |

**UK**

| Breaks | RSS | BIC | LWZ | $SupF_T(k)$ | $SupF_T(l+1|l)$ |
|--------|-----|-----|-----|-------------|------------------|
| 0 | 0.0042 | -9.79* | -9.46* | - | - |
| 1 | 0.0036 | -9.57 | -8.90 | 1.76 | 1.76 |
| 2 | 0.0026 | -9.50 | -8.49 | 2.87 | 3.54 |

Note: The critical values at the 5% level for $SupF_T(k)$ for 1 and 2 breaks are respectively 8.58 and 7.22. The critical values at the 5% level for $SupF_T(l+1|l)$ for l=1 and 2 are respectively 8.58 and 10.13. (R) stands for a rejection of the null hypothesis.

Table 4: Bai Perron (2003) test for multiple breaks

Threshold variable: $Dusa_{t-1}$

## US

| Breaks | RSS | BIC | Breakpoint |
|---|---|---|---|
| 0 | 0.0074 | -9.17* | - |
| 1 | 0.0056 | -9.02 | - |
| 2 | 0.0039 | -8.95 | - |

## China

| Breaks | RSS | BIC | Breakpoint |
|---|---|---|---|
| 0 | 0.0001 | -13.16 | - |
| 1 | 0.0000 | -14.83* | 1984:1 |
| 2 | 0.0000 | -14.72 | - |

## France

| Breaks | RSS | BIC | Breakpoint |
|---|---|---|---|
| 0 | 0.0125 | -8.70* | - |
| 1 | 0.0090 | -8.65 | - |
| 2 | 0.0075 | -8.45 | - |

## Germany

| Breaks | RSS | BIC | Breakpoint |
|---|---|---|---|
| 0 | 0.0208 | -8.19* | - |
| 1 | 0.0167 | -8.03 | - |
| 2 | 0.0143 | -7.81 | - |

## UK

| Breaks | RSS | BIC | Breakpoint |
|---|---|---|---|
| 0 | 0.0074 | -9.17* | - |
| 1 | 0.0056 | -9.02 | - |
| 2 | 0.0039 | -8.95 | - |

Table 5: Test for common LSTAR nonlinearities

| Null hypothesis | Alternative hypothesis | p-value |
|---|---|---|
| The system is linear | At least one of the variables has a LSTAR nonlinearity | 0.026 |
| The system has at most 1 common LSTAR nonlinearity | The system has at least 2 common LSTAR nonlinearities | 0.129 |
| The system has at most 2 common LSTAR nonlinearities | The system has at least 3 common LSTAR nonlinearities | 0.489 |
| The system has at most 3 common LSTAR nonlinearities | The system has at least 4 common LSTAR nonlinearities | 0.887 |
| The system has at most 4 common LSTAR nonlinearities | The system has at least 5 common LSTAR nonlinearities | 0.998 |

Table 6: Estimated nonlinear system

$$Dchi_t = \underset{(0.07)}{1.72}Dchi_{t-1} - \underset{(0.07)}{0.71}Dchi_{t-2} + (\underset{(0.01)}{0.01} + \underset{(0.09)}{0.19}Dchi_{t-1} - \underset{(0.09)}{0.27}Dchi_{t-2}) \times F(Dusa_{t-1}) + \epsilon_{1t}$$

$$Dusa_t = \underset{(0.07)}{1.19}Dusa_{t-1} - \underset{(0.10)}{0.59}Dusa_{t-2} + (\underset{(0.11)}{0.36}Dusa_{t-1}) \times F(Dusa_{t-1}) + \epsilon_{2t}$$

$$Dger_t = \underset{(0.08)}{0.99}Dger_{t-1} + (\underset{(0.02)}{0.01} - \underset{(0.12)}{0.27}Dger_{t-2}) \times F(Dusa_{t-1}) + \epsilon_{3t}$$

$$Dfra_t = -\underset{(0.07)}{0.01} + \underset{(0.14)}{0.61}Dfra_{t-1} + (\underset{(0.01)}{0.02} + \underset{(0.12)}{0.20}Dfra_{t-1}) \times F(Dusa_{t-1}) + \epsilon_{4t}$$

$$Duk_t = -\underset{(0.01)}{0.01} + \underset{(0.12)}{0.46}Duk_{t-1} + \underset{(0.13)}{0.37}Duk_{t-2}+$$
$$+(\underset{(0.01)}{0.02} + \underset{(0.11)}{0.24}Duk_{t-1} - \underset{(0.21)}{0.44}Duk_{t-2}) \times F(Dusa_{t-1}) + \epsilon_{4t}$$

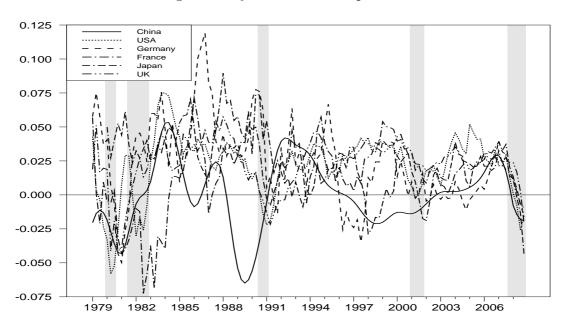where: $F(Dusa_{t-1}) = (1 + exp[-1,90\underset{(0.67)}{}Dusa_{t-1}])^{-1}$

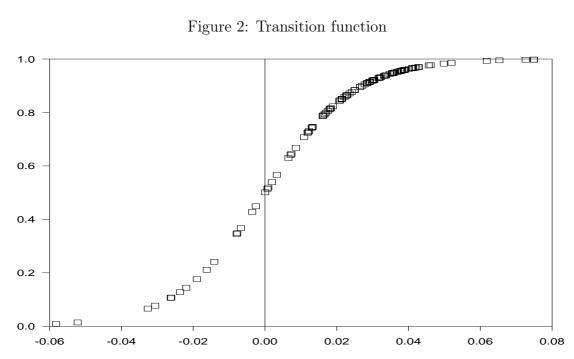Figure 1: Cyclical GDP components
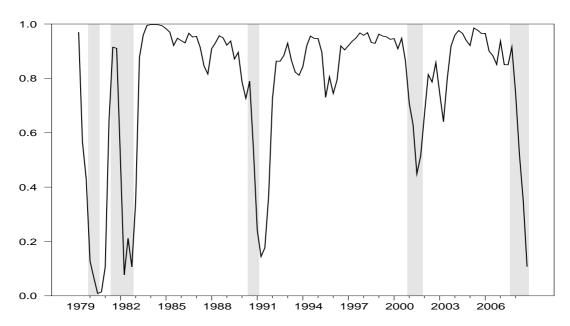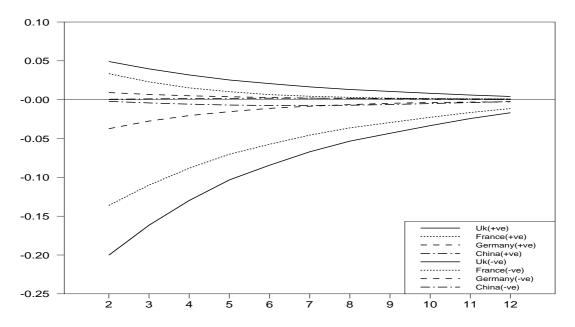
Figure 2: Transition function

Figure 3: Transition function versus time

Figure 4: Impulse response functions



| | | |
|---|---|---|
| —————— | | Uk(+ve) |
| · · · · · · · · | | France(+ve) |
| — — — — | | Germany(+ve) |
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| —————— | | Uk(-ve) |
| · · · · · · · · | | France(-ve) |
| — — — — | | Germany(-ve) |
| — · — · — · | | China(-ve) |