Currency Union, Free-Trade Areas, and Business Cycle Synchronization*

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Abstract

Since the 1970s the characteristics of international business cycles have changed and deeper economic integration has modified the features of cross-country comovement. We formally test for correlation shifts in measures of real economic activity and economic/financial integration. In Europe we find some statistically significant evidence of higher correlations following the creation of the EMU in 1999 for several subgroups of countries. We detect significantly more pronounced correlations between Mexico and the US and between Mexico and Canada in North America after the enforcement of the NAFTA in 1994. Results are derived from an econometric framework based on nonparametric iterated stationary bootstrap methods, whose statistical reliability and performance we assess through Monte Carlo simulations.

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‡Full results and a *Companion Technical Appendix* with a detailed and extended description of the econometric techniques used are available on request or downloadable from `http://sites.google.com/site/pierangelodepace`.

1 Introduction

The past decades have seen substantial real and financial integration among countries. Extent of openness, magnitude of trade volumes, and international financial flows may all have ambiguous effects on business cycle synchronization. Conventional wisdom suggests positive net effects on the degree of cross-country cycle comovement as economic integration gets deeper, but empirical evidence has been, so far, mixed.

In most applied work within the literature on macroeconomic comovement, authors did not formally test for the statistical significance of synchronization variations until a few years ago. Among those who have been testing, the evidence is heterogeneous. For example, Doyle and Faust (2005) apply parametric bootstrap techniques to the series of output, consumption, and investment in the G7 countries, but are not able to detect systematic statistically significant synchronization modifications over the years. Through statistical methods based on a factor-structural vector autoregression ($FSVAR$), Stock and Watson (2005) describe (i) the emergence of two groups of economies – Euro-area and English-speaking countries – characterized by synchronous cycles; and (ii) the declining volatility of common G7 shocks.[1]

In this work we analyze countries in Europe and North America, roughly between the end of the 1970s and the end of 2006, and add to the existing empirical literature on international business cycles in several ways. First, we consider a number of discrete changes that increased international integration to avoid problems of unknown breakpoint testing. We restrict our attention to two major transformations of monetary and trade regimes, the birth of the

[1]Other empirical research has used several and sophisticated statistical tools to detect comovement changes and yet has only led to contrasting conclusions. Agresti and Mojon (2001) extract stylized facts from Euro-area economies that indicate the presence of a significant degree of likeness between European and US cycles. Dueker and Wesche (2003) extend probit models with time-series features such as autoregressive variables and Markov regime switching, use Bayesian techniques, construct new indices, and find that the evolution of correlation coefficients is consistent with the claim that European economies are becoming more harmonized. Artis (2003) constructs structural innovations from three-variable structural VARs, analyzes correlations among European countries, and highlights the presence of a *UK idiosyncrasy*, characterized by increasing similarity of the British cycle to US and Canadian cycles, rather than to European cycles. Artis, Krolzig, and Toro (2004) apply a Markov-switching methodology to series for European economies and suggest that the idea of a European cycle is, indeed, plausible. Preliminary evidence in Del Negro and Otrok (2005) goes against the claim that the monetary union might have increased cycle comovement in Europe. Other significant pieces are Bayoumi and Eichengreen (1992), Coe and Helpman (1995), Artis and Zhang (1997a) and (1997b), Frankel and Rose (1998), Rose and Engel (2000), Bordo and Helbling (2003), and De Grauwe and Mongelli (2005).

European Economic and Monetary Union (EMU) in January 1999 and the enforcement of the North American Free Trade Agreement (NAFTA) in January 1994, and test whether the changes in business cycle synchronization that followed are statistically significant.[2] The use of an exogenously specified breakpoint does not allow us to explore causal relationships, but is natural in the context of evaluating whether changes in integration have been accompanied by shifts in synchronization.[3] Besides, at least in Europe, understanding if business cycles became more synchronized after 1999 – during the first years of the currency union – is relevant *ex post* for optimal monetary policy, regardless of the extent to which we can link the observed comovement changes with the introduction of the common currency itself.[4] Second, we analyze the comovement changes in measures of trade and financial integration – as well as output and other real variables, as in the standard empirical literature – to assess magnitude and nature of convergence (or divergence) across countries and to shed light on the characteristics of international integration. Third, we study the small-sample inference probabilities of the econometric devices we construct for the specific statistical question we intend to answer. Problems with inference on comovement changes are well-known, as argued, for example, by Doyle and Faust (2005), who explain in detail why testing for them is generally difficult, even more so with time-series data. We deviate from previous studies on the subject in terms of econometric techniques and compare the performance of the method we adopt

[2] The analysis described in this work is mainly based on the aforementioned exogenous breaks. However, we also conduct the test on alternative dates. In the case of Europe, January 1994 and July 2000 are considered. January 1994 marks the beginning of Stage II of the EMU, corresponding to the establishment of the European Monetary Institute (EMI). In June 2000 the irrevocable fixed exchange rate between the Greek Drachma and the Euro was determined and Greece officially entered the last stage of its path to the monetary union, which it would complete at the end of December 2000. In the case of the NAFTA countries, we extend our analysis to January 1989, the month beginning from which the CUSFTA – the Canada-United States Free Trade Agreement – was enforced and January 2000. In Section 3.4 we briefly discuss the results associated to these alternative breaks. Moreover, we estimate breaks at unknown dates, providing further evidence in favor of our initial breaks selection.

[3] Bejan (2007) points out the existence of an inversion in the correlation trends of international macroeconomic variables in North America around 1993 or 1994. She constructs a business cycle model with trade costs, calibrates it to the NAFTA countries to estimate the impact of the trade agreement on international synchronization, and shows that comovement increases when trade barriers fall.

[4] Within the traditional OCA (Optimum Currency Areas) theory, a monetary union established among countries with idiosyncratic cycles may not be optimal. Some empirical studies contrast this conventional view. Frankel and Rose (1998), for example, argue that the formation of a monetary union facilitates trade among member countries and reduces the differences in their business cycle. If such effects dominate specialization tendencies, the traditional OCA criteria may prove to be too stringent and member countries may be able to turn themselves into an optimum currency union in the short run or over a sufficiently long period of time.

with alternative approaches within the same class. As a methodological contribution, we provide evidence of its good statistical properties through Monte Carlo experiments.

We define comovement as the unconditional correlation coefficient between two (cyclical) variables and construct a reliable econometric framework to appraise the stability properties of the correlations of stationary business cycle time series following an exogenous date. We apply nonparametric bootstrap methods to the data to generate the testing procedure for the detection of statistically significant correlation variations. There is always a great uncertainty on which resampling scheme is best for inference and on how to use the bootstrap distribution to run tests or construct confidence intervals, especially in a time-series setting. Guided by numerical simulations, we reduce such uncertainty by choosing a specific version of bootstrap, which appears to perform well with the available data. Thanks to the nonparametric approach we are able to analyze at once an extended set of economies and variables, and to study the pairwise cycle synchronization between countries. Monte Carlo experiments show that (i) our ability to identify significant correlation switches is substantial, (ii) the testing strategy is accurate, and (iii) our method is a structure within which reliable inference is achievable even when dealing with short time series.[5]

We show that comovement moderately increased in Europe after the birth of the EMU in terms of real economic activity. Stronger correlations prevailed in several subgroups of countries, among which those in the so-called Deutsche Mark (DM) Bloc, the non-core countries, and some major economies in the European Union (EU).[6] These higher levels of comovement were accompanied by more synchronized financial markets in the core EU countries – whereas the non-core countries, particularly Austria and Belgium, became more isolated – and by significantly more correlated trade volumes (the sum of imports and exports) at the EU level.[7]

[5]Not detecting significant correlation shifts on the basis of a purely statistical procedure is not evidence of stability, though, since the test used may simply have low power. As we describe later in the case of autocorrelated stationary series, with realistic parameterizations of the data-generating processes, we estimate a probability of 76% to reject the null hypothesis of no correlation change when the true shift equals 0.64 and a probability of 55% when the shift equals 0.42.

[6]While most intra-European bilateral exchange rates were rather volatile in the 1980s and 1990s, one group of countries – the Deutsche Mark Bloc – maintained narrow margins of exchange rate volatility.

[7]We will sometimes refer to the following non-mutually exclusive groups of countries within the border of the European Union: core EMU countries (Germany, Spain, France, Italy), core EU countries (core EMU countries plus the United Kingdom), and DM Bloc countries (Austria, Belgium, Germany, Denmark, the

In the NAFTA area we detect higher output and consumption correlations between Mexico and the US following 1994, and significant synchronization increases between Mexico and Canada in consumption, investment, and stock market returns. Output growth rates became significantly less synchronized between Canada and Mexico. With some caveats, we support the view that the episodes of economic and financial integration we consider came with higher levels of macroeconomic synchronization in several areas of the European Union, to some extent in North America.

2 The Econometric Framework: Estimation and Inference

We construct a testing strategy based on the nonparametric iterated stationary bootstrap, which represents a viable solution to attenuate inference problems in small samples with time-series data. The framework is particularly effective in the case of Europe, for which long series are not always existent and only a few years of data can be used to describe the changes that occurred following the birth of the EMU. We extract cycles from the data and test for the significance of correlation changes after exogenous dates. The initial focus is on real output, which we detrend using a multivariate HP filter estimated through a Kalman filter (HPMV) applied over the full sample, and for which we also analyze the rates of growth.[8] We detrend consumption, gross fixed capital formation, and trade volumes using a standard model-free univariate HP filter. Our analysis of financial markets is based on stock market returns.

2.1 A Strategy to Test for Comovement Changes

We define economic cycle comovement as the unconditional correlation coefficient between two series describing the same cyclical measure for two different countries.[9] Let T be the length of

Netherlands).

[8] As in Harvey (1985), Harvey and Jaeger (1993), and Boone (2000), we use semi-structural methods for output gap estimation based on the Kalman filter (KF). For comparison purposes, we employ the Kalman smoother (KS) and two macroeconomic filters conditional on an appropriate macroeconomic production function to obtain alternative cyclical components of output. Hereafter, unless stated otherwise, we will refer to output gaps estimated using the Kalman filter. See Appendix A and the online *Companion Technical Appendix* for details and visit http://sites.google.com/site/pierangelodepace for the complete set of results.

[9] An increase in correlation is commonly interpreted as an increase in the amount of common variation in the economies. However, increases in correlation can also come from decreases in idiosyncratic variation. A

the common sample for those two series, $Br \in (1, T)$ an exogenously imposed breakpoint, and ρ_2 and ρ_1 the correlation coefficients over the subsamples $[Br + 1, T]$ and $[1, Br]$.[10] We test whether the pairwise correlation change (PCC), $\Delta\rho = (\rho_2 - \rho_1)$, is statistically significant by considering the statistical test with size $(1 - \alpha) \in (0, 1)$

$$\begin{cases} H_0 : \Delta\rho = (\rho_2 - \rho_1) = 0 \\ H_1 : \Delta\rho = (\rho_2 - \rho_1) \neq 0 \end{cases}.$$

In general, inference on correlation coefficients and correlation changes is difficult. With time-dependent autocorrelated data and with the relatively small sample sizes available in macroeconomic applications, conventional asymptotics often gives poor approximations to the distributions of estimators and test statistics.[11] The consequence is that the *nominal* probability that a test based on an asymptotic critical value rejects a true null hypothesis and the *true* rejection probability can be very different from each other. Bootstrap techniques represent an alternative way to estimate the distribution of an estimator by resampling available data and treating them as if they were the population. Horowitz (2001) argues that such techniques are often more accurate in finite samples than first-order asymptotic approximations, are not characterized by the algebraic complexity of higher-order expansions, can reduce the finite-sample bias of an estimator, and can also induce significant asymptotic refinements in actual versus nominal coverage and size properties.

An issue to be solved regards the choice of the resampling scheme for the application of the bootstrap. In the *Companion Technical Appendix* we briefly discuss alternative bootstrap schemes. Another issue concerns the definition of the most appropriate testing strategy given the bootstrap distribution. In this work, we bootstrap nonparametrically the difference of the

careful analysis based on unconditional correlations is potentially robust against misspecification problems. The alternative of using specific models to construct comovement measures would instead provide some insight on the causes of synchronization changes.

[10] In this work Br is exogenously imposed. In principle, it could be statistically estimated through maximum likelihood methods or through the maximization (or minimization) of a proper objective function. For example, one might compute Br as the point along the full sample in correspondence to which the estimate of the correlation change, $(\widehat{\rho}_2 - \widehat{\rho}_1)$, is maximized.

[11] See Fisher (1915) and (1921), Gayen (1951), Hotelling (1953), and Hawkins (1989) for inference on correlation changes. Briefly, in a time-series framework and with autocorrelated data, conventional tests are unreliable, since they induce distortions in size and have low power.

correlation coefficients over two contiguous subsamples. Inference is based on the construction of two-sided α-level confidence intervals from the resulting bootstrap distribution. We can thus test for significant variations and infer the direction of the shifts. We set α to the conventional 0.90 (or 0.95) and hold rejections of the null in 10%-level tests as a sign of parameter instability.

Estimating Sampling Distributions via Bootstrap

The idea of nonparametric bootstrap is to draw resamples from the data in a way that preserves their correlation structure. The standard independent bootstrap resamples individual observations and is useful when the data are independent and identically distributed. The block bootstrap randomly resamples blocks of contiguous observations and is more appropriate when the data are time-dependent and nonnegligibly autocorrelated. Blocks resampled in the block bootstrap have a fixed length to be determined and may be either overlapping (moving blocks) or non-overlapping. Regardless of the blocking method, the block length must increase with increasing sample size to make bootstrap estimators consistent. Block size selection involves a trade-off: as block size becomes too small, the bootstrap destroys the time dependency of the data and its accuracy falls; as block size becomes too large, there are fewer blocks and pseudo-data tend to be similar to each other, which results in a decline of the average accuracy of the bootstrap. This means that there exists a critical value of the block length that minimizes the mean squared error of the bootstrap estimator.[12]

Politis and Romano (1994) propose a way of resampling, the *stationary bootstrap*, that preserves stationarity, removes some of the distortions that emerge from the moving-blocks bootstrap, and ensures consistency and weak convergence within the resampling. The stationary bootstrap resamples blocks of random length from the data. The length of each block is sampled from an independent geometric distribution whose expected value equals the expected

[12] The bias of a bootstrap estimator is the difference between the mean of the bootstrap estimates and the sample estimate of the parameter from the original dataset. The standard error, SE_{Boot}, of a bootstrap statistic is the standard deviation of the bootstrap distribution of that statistic. According to Efron and Tibshirani (1993)'s rule of thumb, a bias of less than $0.25SE_{Boot}$ can be ignored. The mean squared error of a bootstrap estimator equals the variance of the bootstrap estimator plus the square of its bias.

block size. Politis and Romano (1994) suggest that the original series should be *wrapped* around a circle to fill blocks going past the last observation.[13] Camacho, Perez-Quiros, and Saiz (2005) use the stationary bootstrap to analyze if each European country presents business cycles that are similar enough to validate what some authors call the European cycle. Our estimates and inference are based on the version of stationary bootstrap that follows. Formally, in the case of two countries, A and B, let $V_{A,t} = \{V_{A,s}\}_{s=1}^{T}$ and $V_{B,t} = \{V_{B,s}\}_{s=1}^{T}$ denote two observed time series (cycle measures), with Br being an exogenous breakpoint that splits each series into two subsamples, $V_{A,t}^{1} = \{V_{A,s}\}_{s=1}^{Br}$, $V_{B,t}^{1} = \{V_{B,s}\}_{s=1}^{Br}$, $V_{A,t}^{2} = \{V_{A,s}\}_{s=Br+1}^{T}$, and $V_{B,t}^{2} = \{V_{B,s}\}_{s=Br+1}^{T}$. In the first subsample, let $w_{A,i,l}$ and $w_{B,i,l}$ respectively denote the blocks $\left\{V_{A,s}^{1}\right\}_{s=i}^{i+l-1}$ and $\left\{V_{B,s}^{1}\right\}_{s=i}^{i+l-1}$ of length l starting at $V_{A,i}^{1}$ and $V_{B,i}^{1}$, with $V_{A,i}^{1} = V_{A,1+\{(i-1) \bmod Br\}}^{1}$, $V_{B,i}^{1} = V_{B,1+\{(i-1) \bmod Br\}}^{1}$, $V_{A,0}^{1} = V_{A,Br}^{1}$, and $V_{B,0}^{1} = V_{B,Br}^{1}$. Let $I_1, I_2, ...$ be a stream of random numbers uniform on the integers $1, ..., Br$, and let $L_1, L_2, ...$ be a stream of random numbers independently drawn from a geometric distribution, $Prob\,(L = l) = \lambda\,(1-\lambda)^{l-1}$ with $l = 1, 2, ...$ The inverse of λ is the expected block length, $E\,(L) = \frac{1}{\lambda}$, to be selected.[14] Given $\widehat{\left(\frac{1}{\lambda}\right)}$, the algorithm to generate a couple of stationary bootstrap time series replicates over the first subsample, $V_{A,t}^{1*}$ and $V_{B,t}^{1*}$, runs as follows: (i) set $V_{A,t}^{1*} = w_{A,I_1,L_1}$, $V_{B,t}^{1*} = w_{B,I_1,L_1}$, and $j = 1$; (ii) while $length\left(V_{A,t}^{1*}\right) < Br$, increment j by 1 and redefine $V_{A,t}^{1*}$ and $V_{B,t}^{1*}$ as $V_{A,t}^{1*} := V_{A,t}^{1*} \cup w_{A,I_j,L_j}$ and $V_{B,t}^{1*} := V_{B,t}^{1*} \cup w_{B,I_j,L_j}$; (iii) if $length\left(V_{A,t}^{1*}\right) > Br$, discard the two series of pseudo-data just generated and restart resampling from (i) after drawing new streams of I_j's and L_j's. We repeat this scheme N^B

[13] A series resampled with the (overlapping or non-overlapping) block bootstrap is nonstationary, even if the original series is strictly stationary, because the joint distribution of resampled observations close to a join between blocks differs from that in the center of a block. The stationarity of the observations obtained through the stationary bootstrap does not contribute significantly to the reduction of the bias of the resulting bootstrap estimators. At least asymptotically, the same amount of bias is generated using either overlapping or non-overlapping blocks and either fixed or random block lengths. Differences may arise in small samples.

[14] A data-based choice for λ is necessary and should be based on some rule. In general, λ should satisfy (i) $\lambda \to 0$ and (ii) $\lambda Br \to \infty$, as $Br \to \infty$. If these two conditions are respected, the choice of λ will not affect the first-order properties, such as bias or coverage error, of the bootstrap estimators. Getting the right rate for λ to tend to 0 affects the second-order properties.

A set of smaller bootstraps, run before the implementation the main routine, is used to select the expected length. Each of these bootstraps is based on a different expected length, allowed to vary over a closed interval of consecutive integers, whose boundaries are proportional to the sample size. For each smaller bootstrap we estimate the (root) mean squared error. The expected block length that produces the smallest (root) mean squared error is chosen. Horowitz (2001) provides the theoretical rates at which the block length should increase if the objective is to minimize the asymptotic (root) mean squared error of the bootstrap estimator.

times for both the first and the second subsamples. At each complete resample of the original data, we estimate and collect $\widehat{\Delta\rho}^* = \left\{ corr\left(\widehat{V^{2*}_{A,t}, V^{2*}_{B,t}}\right) - corr\left(\widehat{V^{1*}_{A,t}, V^{1*}_{B,t}}\right) \right\}$ to compose the bootstrap distribution of $\widehat{\Delta\rho}$.[15]

Constructing Confidence Intervals

We construct intervals for $\Delta\rho$ from bootstrap distributions and exploit the dual relationship between hypothesis testing and interval estimation to detect changes in cycle comovement.[16] Any method for obtaining confidence intervals requires some conditions – rarely met in practice – to produce the intended confidence level. It is known that t methods generally perform better than percentile.[17] Hall (1995) argues, however, that this is not the case with sample correlation coefficients, for which the percentile method is more appropriate, although it still provides a poor coverage accuracy. One way to solve the problem is to use bootstrap iteration, which enhances the accuracy of bootstrap techniques by estimating an error term – the coverage error of a confidence interval – and by adjusting the method so as to reduce that error.[18] One advantage is that it may substantially improve the performance of naïve bootstrap methods. In the case of percentile methods, it retains their stability properties and increases their coverage accuracy through the adjustment of nominal levels or interval endpoints. An obvious drawback is that iteration is highly computer intensive.

The nominal α-level bootstrap percentile confidence interval for $\Delta\rho$ is the interval between the $\left[100 \times \frac{\varrho_\alpha}{2}\right]$-th and the $\left[100 \times \left(1 - \frac{\varrho_\alpha}{2}\right)\right]$-th percentile of the bootstrap distribution of $\widehat{\Delta\rho}$, where ϱ_α is the adjusted nominal level that brings the coverage closer to the desired level, α. An estimate for ϱ_α is obtainable through an additional round of bootstrapping. Bootstrap

[15]The standard independent bootstrap is a block bootstrap with the block length equal to one. It is a degenerate case of stationary bootstrap where $Prob\,(L = 1) = 1$. We use it when analyzing non-autocorrelated time series as structural innovations.

[16]We construct two-sided, equal-tailed intervals – i.e., we attempt to place equal probability in each tail.

[17]In general, the percentile method performs well for unbiased statistics; with biased statistics, it amplifies the bias. Efron and Tibshirani (1993) show that, under some regularity conditions, the percentile method is first-order accurate, which means that the error of confidence interval coverage approaches zero at a rate related to $\frac{1}{\sqrt{\min(Br, T-Br)}}$. See the *Companion Technical Appendix* for a brief discussion of some methods alternative to the percentile.

[18]The coverage error is the difference between the nominal coverage probability of a confidence interval and its true coverage probability. The coverage error is often substantial in empirical applications, particularly when the bootstrap distribution is not symmetric.

iteration improves the accuracy of confidence intervals through nested levels of resampling to be used to estimate the coverage error and obtain a more precise coverage.[19] In formal terms, let $V_{A,t}$ and $V_{B,t}$ be two variables and $I_0\left(\alpha; V_{A,t}, V_{B,t}; V^*_{A,t}, V^*_{B,t}\right)$ the uncorrected bootstrap percentile confidence interval of nominal coverage probability α for the associated $\Delta\rho$. $V^*_{A,t}$ and $V^*_{B,t}$ are two resamples with replacement from $V_{A,t}$ and $V_{B,t}$, so that I_0 is constructed from sample and resample information. In applied work, the coverage probability of I_0, $P(\alpha) = Prob\left\{\Delta\rho \in I_0\left(\alpha; V_{A,t}, V_{B,t}; V^*_{A,t}, V^*_{B,t}\right)\right\}$, often differs significantly from α. There exists a real number, ϱ_α, such that $P(\varrho_\alpha) = \alpha$. Let $I_0\left(\alpha; V^*_{A,t}, V^*_{B,t}; V^{**}_{A,t}, V^{**}_{B,t}\right)$ be a version of $I_0\left(\alpha; V_{A,t}, V_{B,t}; V^*_{A,t}, V^*_{B,t}\right)$ computed using information from $V^*_{A,t}$, $V^*_{B,t}$, $V^{**}_{A,t}$, and $V^{**}_{B,t}$; $V^{**}_{A,t}$ and $V^{**}_{B,t}$ are resamples with replacement of $V^*_{A,t}$ and $V^*_{B,t}$. An estimate of $P(\alpha)$ is $\widehat{P}(\alpha) = Prob\left\{\widehat{\Delta\rho} \in I_0\left(\alpha; V^*_{A,t}, V^*_{B,t}; V^{**}_{A,t}, V^{**}_{B,t} | V_{A,t}, V_{B,t}\right)\right\}$.

Let N^B_O be the number of bootstrap replications at the outer level of resampling; we calculate $\widehat{P}(\alpha)$ as $\widehat{P}(\alpha) = \frac{\sum_{n^B_O=1}^{N^B_O} 1\left\{\widehat{\Delta\rho} \in I_{0,n^B_O}\left(\alpha; V^*_{A,t}, V^*_{B,t}; V^{**}_{A,t}, V^{**}_{B,t}\right)\right\}}{N^B_O}$. Since distribution information on $V^{**}_{A,t}$ and $V^{**}_{B,t}$ given $V^*_{A,t}$ and $V^*_{B,t}$ is unavailable, we use an inner level of resamples (say, N^B_I resamples for each outer resample, n^B_O) from $V^*_{A,t}$ and $V^*_{B,t}$ to outline the features of that distribution.[20] The bootstrap estimate for ϱ_α is the solution, $\widehat{\varrho}_\alpha$, to the equation $\widehat{P}(\varrho_\alpha) = \alpha \therefore \widehat{\varrho}_\alpha = \widehat{P}^{-1}(\alpha)$.[21] The iterated bootstrap confidence interval for $\Delta\rho$ is then $I_1\left(\widehat{\varrho}_\alpha; V_{A,t}, V_{B,t}; V^*_{A,t}, V^*_{B,t}\right)$.

3 Empirical Results

Theory does not provide clear predictions on the relation between international economic integration and macroeconomic comovement. Intense trade tends to be associated with highly correlated business cycles in a wide range of theoretical models – for example, multi-sector

[19] DiCiccio, Martin, and Young (1992).

[20] $N^B_O = 1,000$ for the outer block bootstrap; $N^B_I = 500$ for the inner bootstrap. With bootstrap iteration, $N^B = N^B_O$. When iteration is not used, in the case of the standard independent bootstrap, $N^B = 10,000$. Bootstrap samples are drawn using the same nonparametric method in the main and nested bootstraps.

[21] With discrete variables and discrete bootstrap distributions, an exact solution for this equation can not always be found, unless we use smoothing techniques. We choose the smallest value, $\widehat{\varrho}_\alpha$, such that $\widehat{P}(\widehat{\varrho}_\alpha)$ is as close as possible to α, i.e., such that $\left|\widehat{P}(\varrho_\alpha) - \alpha\right|$ is minimized over a grid of values and additional conditions defining tolerance are satisfied.

international models with intermediate goods trade and one-sector models with either technology or monetary shocks. The removal of trade barriers should, in principle, facilitate the diffusion of demand shocks, technology, and knowledge spill-overs and lead to more synchronous output cycles. On the other hand, the *specialization paradigm*, based on standard Heckscher-Ohlin trade theory, predicts the emergence of asynchronous output cycles with free trade, as a consequence of the larger exposure of countries to asymmetric, industry-specific supply shocks due to deeper specialization in production. But, if countries exhibit a trend towards intra- rather than inter-industry trade, the implied effects may be different: either if intra-industry trade is vertical or horizontal, then industry-specific shocks may make business cycles more synchronized. Theoretical arguments lead to heterogeneous conclusions also in the case of consumption, depending on the level and the nature of integration among countries, although standard models tend to predict higher consumption correlations with complete markets and full economic and financial integration. As for investment, even when countries converge to full integration, factors and dynamics ambiguously act on correlations, which may be affected by the intensity and nature of economic or productivity shocks and spill-over effects. In autarky, output and investment are related to consumption smoothing; with integration in international markets, trade and asset flows impact on consumption insurance and the link between output/investment and consumption may get weaker.[22]

In the case of the currency union in Europe, assessing the extent to which synchronization changed after 1999 is relevant for optimal monetary policy. In the case of North America, some research shows that trends in comovement changed around 1994. Our attempt is to give an answer to what is essentially an empirical question and to assess the direction and the magnitude of the cycle synchronization variations that followed the aforementioned episodes of international integration for the countries in the sample.

[22] While one view is that causation runs from events of economic integration to shifts in business cycle correlations, it is also possible that such shifts occur due to trends in the underlying structure of production and that, for instance, the formation of a currency union is endogenous to these trends, maybe because countries among which macroeconomic comovement is high face fewer costs from adopting a single currency and a single monetary policy. If this is the belief, rather than exogenously imposing Br, one should estimate it first and then test for the significance of the correlation change over the two resulting subsamples.

3.1 The Data

We include the twelve original EMU countries (EMU12) plus Denmark, Sweden, and the United Kingdom (EU15); the USA, Canada, and Mexico. The set of EMU countries excludes Estonia, Slovenia, Slovakia, Malta, and Cyprus, which joined the monetary union more recently. Denmark, Sweden, and the United Kingdom are currently outside the currency union, but were already part of the EU on the date of introduction of the Euro.[23] Table 1 sums up the degree of integration of the surveyed countries along two dimensions, participation in major trade agreements and exchange rate regime.

The series of output, consumption, gross fixed capital formation, and trade volumes are quarterly and seasonally adjusted.[24] Data on stock market indices are monthly. The span of the econometric investigation is between the end of the 1970s (EU) or the beginning of the 1980s (NAFTA) and the end of 2006. Samples start later or exclude countries in those exercises including variables for which longer or entire series are unavailable. The exogenous breakpoints are 1998.4 for the EU/EMU and 1993.4 for the NAFTA.[25] Extending the sample to include the recent global downturn is an option that we defer to future research. There is evidence, though, that the last recession was highly synchronous, since peaks and troughs occurred almost at the same time in the world major economies.

The data for EU countries and the USA are generally from EUROSTAT; US final consumption expenditure is from the OECD. The series for Canada are from the Canadian National Statistical Agency; its final consumption expenditure series is from the OECD. The Mexican data are collected from the Instituto Nacional de Estadística Geografía e Informática. The series on gross fixed capital formation for Mexico and Canada come from

[23] The Danish currency is pegged to the Euro. The birth of the EMU might have affected the synchronization of the British and Swedish cycles with the rest of the EMU countries through a real exchange rate channel.

[24] One could argue that a weakness in the use of the HP filter on seasonally adjusted data is the treatment of structural breaks. The HP filter and the algorithm for seasonal adjustment might smooth out their effects over the sample, making, in principle, the detection of breakpoints harder. However, using seasonally adjusted data (and/or data filtered in some way) is common practice in most empirical studies, also when one looks for structural breaks in the growth rates, or the detrended versions, of macroeconomic aggregates. Some recent theoretical and empirical literature (see, for example, Sims, 1993; Ghysels and Perron, 1996; Kaiser and Maravall, 1999; Ahumada and Garegnani, 2000; Maravall and del Rio, 2001; Ghysels, 1998; Mir and Osborn, 2004) shows that it is not clear that raw, seasonally unadjusted data should be used, instead, or that the HP filter should be avoided, when the goal is to estimate (or test for) structural breaks.

[25] With monthly data (stock markets), the breakpoints are 1998.12 and 1993.12, respectively.

the OECD. A complete description of the dataset is available in the *Companion Technical Appendix*.

3.2 The Real Economy

We analyze the real economy by looking at international bilateral correlations between output, consumption, and investment, and report the cross-correlation changes and corresponding inferences in the tables at the end of the article. What follows is a qualitative summary of select results.

Output, Consumption, and Investment

EU15/EMU12. Tables 2 and 3 show the outcomes for European countries. Point estimates of pairwise correlation shifts are generally positive in the EU, as well as in the EMU. A vast majority of the many significant changes are positive for almost all business cycle measures. This pattern is clear with real output (gap and growth rate, Table 2) and gross fixed capital formation (lower panel in Table 3). We obtain qualitatively similar results and inferences, not reported in this paper, when the cyclical components of real GDP are estimated using alternative methods (i.e., the Kalman smoother and the macroeconomic filters). In the case of final consumption expenditure (upper panel in Table 3), we find a prevalence of positive point correlation shifts in the EU, whereas small proportions of significant changes are similarly split between ups and downs. We detect a higher incidence of significantly negative switches in the monetary union. The empirical findings on gross fixed capital formation and consumption are in contrast with main-stream economic theory, though. On the one hand, stochastic dynamic international business cycle models with country-specific technology shocks predict that stronger trade and financial linkages should lead to lower investment comovement across countries, as capital and other resources should move to countries experiencing positive technology shocks. On the other hand, standard theoretical literature on risk-sharing predicts higher levels of comovement in consumption as integration among countries gets deeper and markets get closer to be complete. However, recent theoretical literature has challenged such conclusions.[26]

Overall, the results indicate parameter instability and a tendency to significant increases in correlations among some subgroups of countries. This tendency does not concern only the countries that adopted the Euro. A closer examination shows that, in frequent instances, significant increases regard some of the biggest economies in the EMU. For example, this is the case of Germany and Italy (output gap and growth rate), Spain and Germany (output gap and gross fixed capital formation), Italy and the Netherlands (output gap and growth rate), Germany and the Netherlands (output gap, final consumption expenditure, gross fixed capital formation), Spain and the Netherlands (output gap). At the EU level we find signs of stronger comovement between the UK and France, Germany, Spain, and Italy in terms of output. This piece of evidence reveals the deep linkages between the UK and continental Europe, despite the opt-out clause that still allows the country to be out of the Euro-area.[27]

Worth of mention are the nonnegligible rises in comovement between Denmark and several EU countries as for all the real variables discussed in this section. Of additional interest is the case of the countries in the DM Bloc and Finland, for which the comovement of output, investment, and trade significantly rose in many instances after 1999. The countries in the DM zone were part of a single-currency arrangement already in the 1980s. Therefore, high levels of pre-1999 synchronization and only small, possibly non-significant, increases in comovement would be expected within the DM Bloc, if one believes in the story that economic integration and high business cycle correlations should come together. However, this is not what we observe in the data. Perhaps the relationship between economic integration and business cycle correlations, if true, is non-linear.

NAFTA. Table 5 is a summary for the NAFTA countries. To some extent, the agreement enhanced comovement in North America. The evidence is in favor of a more pronounced

[26] Kaminsky (2005) claims that economic and financial integration does not ensure perfect smoothing in private consumption and that procyclical net capital flows tend to act as a source of aggregate volatility.

[27] Baldwin (2006) notes that countries do not need to be inside the Euro-area to benefit from most of its economic gains and to be directly affected by its dynamics. EMU countries also increased their trade with the UK, Denmark, and Sweden. In principle, outsiders ought to benefit from fewer moneys and fewer units of account in the EMU. The UK, Denmark, and Sweden should do so more than most countries, on average, since they trade far more with the EMU members than the average non-member does.

synchronization between Mexico and the USA in terms of output (gap) and consumption. Other significantly positive shifts regard Canada and Mexico in consumption and fixed capital formation; output growth rates became significantly less correlated. No significant changes are detected between Canada and the USA. One could argue that, despite the dramatic increase in trade and the deep economic integration with the US, which started much earlier than 1994, the contextual Canadian specialization might have compensated the tendencies to higher synchronization.

Structural Innovations

Economic integration alters the synchronization of output through diverse channels. Frankel and Rose (1998) argue that policy shocks are likely to become more correlated when barriers to trade are removed and coordinated supranational economic policies are enforced. This view, however, does not have a wide consensus.

We use structural vector autoregressions ($SVAR$) and long-run restrictions to decompose the variance of a vector of economic variables and derive structural supply and demand (fiscal and monetary) shocks as described in the *Companion Technical Appendix*. We employ two different VAR specifications. The first is appropriate to identify basic structural innovations in a closed economy, the second – as Clarida and Gali (1994) point out – may better fit the case of an open economy and is, perhaps, more meaningful in the present context.

In Europe, under the first model specification, the evidence on comovement changes is mixed, as point estimates almost equally split between increases and decreases.[28] This finding contradicts the claim that the formation of a currency union should generally lead to more symmetric economic shocks.[29] Statistically significant shifts appear in proportions between 12.1% and 15.2% within the EU, with no clear pattern in the direction. Similar conclusions hold for the EMU countries, for which the incidence of significant changes ranges between 11.1% and 16.7% of the total number of observations. Despite a weak prevalence of negative switches in the correlation of supply and demand (monetary) shocks of the second type and

[28] The tables with the relevant results can be found online.

[29] See De Grauwe and Mongelli (2005) for a survey.

a weak majority of positive correlation shifts in demand (fiscal) shocks of the first type, such results do not lead to an unambiguous interpretation.

Under the second VAR specification, the changes in the correlation of monetary shocks are positive and significant in nonnegligible proportions – 43.9% at the EU level, 52.8% at the EMU level. We find some weak evidence that fiscal structural shocks became pointwise less correlated after 1998.4, significantly so in the proportions of 10.6% and 13.9% of the total number of shifts at the EU and EMU levels, respectively.

3.3 Trade and Financial Markets

As economic integration gets stronger, the comovement features of international trade volumes are expected to change.[30] As countries open up to trade, their economic linkages strengthen, with effects on cycle transmission. A few articles have treated correlations in capital markets and other measures of international financial integration. Financial integration may enhance risk-sharing among countries, but also lead to specialization and negatively affect cycle synchronization. Arguments predicting opposite effects do exist and, in fact, the empirical evidence on the linkages among international stock markets has been conflicting so far. Results vary, depending on the choice of markets and indices, the sample periods, the frequency of observations, and the techniques of analysis. One may wonder whether and how the relatively recent economic and financial integration modified the nature or the intensity of these links among countries. We address these issues in the next sections.

Trade Volumes

EU15/EMU12. Total trade flows became more correlated in Europe after 1999. About 95% of point estimates show correlation increases both in the EU as a whole and in the EMU economies. Almost a third (28.8%) of the total number of correlation changes are significantly positive in the EU, more than a third (38.9%) in the common-currency area

[30] EU trade share within the Union is between 60% and 65% of total trade activity (source: European Commission, January 2007), which suggests the presence of similar trade patterns among member countries. This intuition is corroborated by the generally high correlations between trade volumes.

(upper panel in Table 4). Significant rises involve most of European countries, including the largest economies. These findings witness more integration in real markets, despite the fact that many European countries had already been open up to trade for decades, since the birth of the Economic Community.

NAFTA. Table 5 does not provide similarly strong evidence for the NAFTA region: the point estimates of correlation changes in trade volumes are positive – but of small entity – between Mexico and Canada and between Mexico and the USA; the corresponding figure is small and negative between Canada and the USA. In none of these cases are we able to identify statistically significant shifts. Thus, the effects, if any, of the trade agreement on comovement among these variables were negligible for the three countries. However, total trade activities were already strongly correlated before the more recent episode of integration.

Stock Markets

EU15/EMU12. In the lower panel of Table 4 we examine the comovement changes in monthly stock market returns for the European countries. The returns are calculated as $R_t = \log\left(\frac{Ind_t}{Ind_{t-1}}\right)$, where Ind_t is the monthly stock market index at time t. The point estimates are negative in the majority of cases. Falls and rises show up in similar proportions, if we look only at statistically significant variations. We might conclude that the correlations in European financial markets did not increase since the creation of the currency area or that evidence is still inconclusive. However, a few significant rises provide support for the claim that at least the largest markets in terms of domestic capitalization became more synchronous after 1999. It is the case for Germany and France, Germany and Spain, Germany and the UK, the Netherlands and France, Italy and France, the UK and the Netherlands, Finland and France. On the other hand, smaller markets like Austria and, maybe, Belgium became significantly more isolated. The emergence of a core of countries and the formation of a peripheral group in European financial markets is a plausible description of the situation.

NAFTA. Table 5 shows results for stock markets in the NAFTA area: only between Canada and Mexico can we spot a significant increase in the correlation of monthly returns, but comovement between US and Canadian markets was already high before 1994.

3.4 Alternative Break Dates

We conduct the same investigation using alternative dates. In the case of Europe, January 1994 and July 2000 are additionally considered. In the case of the NAFTA countries, we also focus on January 1989 and January 2000.[31] With the alternative dates we detect a smaller number of significant changes in the bilateral correlations of European macroeconomic aggregates. Evidence of the same kind, perhaps less clearly, is found in the structural innovations, especially those estimated under Clarida and Gali's VAR specification. In North America, the beginning of the new century was accompanied by significant comovement increases between Canada and Mexico and between Mexico and the USA in terms of output and consumption. On the other hand, a significant fall in the synchronization of output growth rates occurred between the USA and Canada, compensated by a significantly positive shift in the correlation of investment series.

Looking for evidence that could reinforce the argument proposed in the previous sections and justify our initial selection of breakpoints, we test for breaks at unknown dates in GDP. We adopt Qu and Perron (2007)'s approach to identify one or two breaks in the coefficients and innovation variances of two $VAR(1)$ models including either the detrended outputs or the output growth rates of five European countries (Germany, Italy, France, Spain, and UK) and, separately, the NAFTA countries.[32] The breaks and the corresponding confidence intervals are estimated by maximum likelihood. Pointwise, the identified breaks are close to those used in the main analysis. Furthermore, we find that the confidence intervals, estimated at conventional levels, cover 1998.4 in Europe and 1993.4 in the NAFTA area. These results and

[31] The alternative breaks in Europe are 1993.4 and 2000.2 (1993.12 and 2000.6 with monthly data), in North America 1988.4 and 1999.4 (1988.12 and 1999.12 with monthly data). The results of this additional piece of analysis are not reported in this article, but are downloadable from `http://sites.google.com/site/pierangelodepace`.

[32] Estimating VAR models including all countries in the EU is not feasible for two reasons: 1) there exists some degree of heterogeneity in the sample sizes that has to be taken into account; 2) given the relatively short samples, the estimation of models with too many parameters is impractical. As of the end of 2006, though, the total GDP of the five countries included in the European VARs represented 78% of the GDP of the fifteen EU countries in the dataset.

the pattern emphasized under the alternative break dates are reassuring empirical evidence that 1998.4 and 1993.4 are "*good*" breakpoints for the proposed empirical investigation.

4 Reliability of the Testing Strategy – Monte Carlo Evidence

As far as the application of the nonparametric bootstrap is concerned, whether block or stationary bootstrap is better in practice is a bit of an open question. Econometric theory does not provide us with clear indications on which resampling scheme to adopt in any given circumstance. For some particular statistical problems, Lahiri (1999) finds that the asymptotic mean squared error of the stationary bootstrap estimator exceeds that of the bootstrap with non-stochastic block lengths, regardless of whether the blocks are overlapping or non-overlapping and under the assumption that the block length is optimally chosen – i.e., the block length minimizes the mean squared error of the bootstrap estimator. On the other hand, Politis and Romano (1994) argue that the choice of the expected block length in the stationary bootstrap is not as crucial for consistency as in the other block bootstrap schemes. This finding results into an attenuation of the severity of the trade-off between consistency and efficiency when using stationary bootstrap estimators. The implication is that, in block resampling schemes with fixed block lengths, if the block length is not correctly chosen, the bootstrap may lead to inconsistent estimators and incorrect inference. This feature of bootstrap schemes is not of secondary importance, since the optimal block size is never known in practice and the (expected) block size used in applications is likely to be suboptimal most of the times. The theoretical consequences of our specific choices – i.e., the use of a block bootstrap with random block lengths and the algorithm for the selection of the expected block length – in such a complex empirical application are difficult to assess. A mathematical analysis of the proposed procedure would be very demanding and go beyond the scope of this work. From a practical point of view, however, we can study its features by numerical simulations.

In general, despite its high consumption of computer resources and time, the bootstrap approach should be preferred to conventional asymptotics to address the specific statistical question we consider, given the characteristics of the dataset.[33] We explore the properties of the method we propose for inference and compare it to alternative, commonly used, bootstrap solutions.[34] To assess the reliability and small-sample properties of alternative resampling schemes and bootstrap confidence intervals, we design proper Monte Carlo simulations, which guide us to the selection of a preferred method to derive intervals from actual data and produce evidence that the iterated stationary bootstrap is an appropriate statistical tool for our framework. We estimate empirical coverage probabilities for bootstrap confidence intervals, examine the characteristics of correspondent two-sided tests, and evaluate their statistical power. We report results for a number of resampling mechanisms and data-generating processes (DGPs) with realistic parametrization, including a robustness check with heteroskedastic errors to simulate the presence of the Great Moderation in the data, and eventually opt for the scheme that generates negligible bootstrap biases, produces intervals with actual coverage probabilities close to nominal levels (a $\pm 5\%$ tolerance band for the actual coverage probability around the nominal level is acceptable in empirical works), and induces high statistical power in the corresponding tests.

We find that, with autocorrelated series, the iterated stationary bootstrap performs a bit better than the other resampling mechanisms and generates a testing device that is reliable in terms of estimated coverage probabilities.[35] The iterated standard independent bootstrap proves to be adequate for data with no autocorrelation, although it seems to induce less power in the test than the standard independent bootstrap with no iterations. Tables 6a-c report the results from the Monte Carlo experiments and show that our method has better size properties than the others while retaining good power. We conclude that our ability to identify significant correlation switches is nonnegligible and that our testing strategy is

[33] Depending on the sample size, the inference on one simple correlation coefficient based on the iterated stationary bootstrap algorithm is obtainable in approximately 45-90 minutes of machine time in MATLAB on a Pentium M, 2.13GHz computer.

[34] An informal assessment of the properties of the testing strategy is described in the *Companion Technical Appendix*, where we discuss a direct comparison of our methodology with that used in Doyle and Faust (2005).

[35] We compare the performance of the following bootstrap schemes: standard independent, non-overlapping block, overlapping block, stationary, iterated standard independent, iterated overlapping block, iterated stationary, and iterated parametric (under the assumption of correct specification). See Appendix B for a description of the procedure and of how artificial data for simulations are generated through alternative DGPs.

accurate also when samples are small.[36]

5 Conclusions

In this paper we extract cyclical information from macroeconomic data. Then we construct and assess the reliability and the relative performance of an econometric framework, mainly based on nonparametric stationary bootstrap techniques, useful for the analysis of correlation shifts following an exogenously chosen date and for the determination of whether that date is a structural break in the parameter(s) of interest. Monte Carlo simulations show that the version of iterated stationary bootstrap we use is reliable in a time series setting and performs satisfactorily with relation to the statistical and economic questions we address.

We apply our econometrics to two groups of countries and pick two major changes in international economic integration, the birth of the European EMU and the introduction of the NAFTA. Alternative break dates are also considered and briefly discussed. We find significant signs of higher levels of cycle synchronization in Europe after the introduction of the Euro, despite the large correlations already prevailing in the area in the pre-EMU period. Our inference shows higher degrees of comovement in several areas, among which the countries in the DM Bloc plus Finland and non-core EU economies.[37] We identify significantly positive pairwise correlation switches among EU countries in nonnegligible proportions (often between large EMU countries and countries outside the currency union, Denmark and the UK in particular). The empirical evidence is consistent with the claim that the formation of the Euro-area was followed by stronger economic integration in real markets and by moderately more evident comovement of real economic variables. Financial integration, measured by the synchronization of stock markets, exhibits a peculiar pattern: correlations became stronger among core countries, whereas a peripheral group of non-core countries (especially Austria and Belgium) became more isolated over time.

[36] The standard-sample-size Monte Carlo experiment running an iterated stationary bootstrap algorithm takes between 25 and 40 days of machine time in MATLAB on an Intel Core 2, 1.86GHz computer. Experiments are slightly faster under the alternative bootstrap schemes.

[37] Finland was not part of the DM Bloc. However, its geographical proximity to the countries in the Bloc within the borders of the EU might have affected the behavior of its business cycles.

In North America, we detect increased pairwise comovement in output and consumption between Mexico and the US, and between Mexico and Canada in consumption, gross fixed capital formation, and stock market returns. The finding on consumption is evidence of increased consumption risk-sharing in the area. Output growth rates became significantly less synchronized between Canada and Mexico. The minimal size of the impact of the NAFTA for the US economy could be expected, since the United States had very low tariffs even before the trade agreement.

International integration is an ongoing process and an answer to the question of whether the moderately higher degree of cross-country synchronization we find after the selected breaks is transitory or permanent should be left to future studies. Our results do not suggest that globalization and integration induced more pronounced cycle synchronization across the countries in the sample. Rather, they show that the features of macroeconomic comovement and its changes may be heterogeneous, different in kind, and crucially depending on the nature of the analyzed variables. Similarity in comovement and tendencies to higher synchronization often appear to be characteristics of clusters of countries with common traits and peculiar economic links. Furthermore, if we believe that seasonally adjusted and filtered data bias the analysis, then they likely bias it in favor of finding a lower number of significant correlation changes. After all, our testing device may simply be not powerful enough, but failing to reject the null of no comovement change is not evidence of no change at all. Despite the small samples, though, we succeed in detecting a nonnegligible set of significantly more correlated variables. All this considered, the point made in this work appears even stronger.

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7 Technical Appendix

We sketch some of the econometric techniques used in the paper. For further discussion and details, refer to the *Companion Technical Appendix.*

Appendix A. The Kalman Filter/Smoother and the Hodrick-Prescott Filter

In the multivariate HP filter, the minimization problem for potential output estimation is

$$\min_{\{y_t^*\}_{t=1}^{T^*}} \sum_{t=1}^{T^*} \left\{ \left(y_t - y_t^*\right)^2 + \lambda_1 \left(\Delta y_{t+1}^* - \Delta y_t^*\right)^2 + \lambda_2 \left(\xi_t\right)^2 \right\}, \qquad (A.1)$$

where y_t is the logarithm of the level of real GDP and y_t^* is potential output.[38] The ordinary HP filter is augmented with the residuals, ξ_t, of an economic relationship that incorporates useful information for output gap extraction

$$y_t' = \beta y_t^* + \overline{\gamma}_K^T F_t + \xi_t, \tag{A.2}$$

where y_t' is explainable by unobserved potential output, y_t^*, and by a set of K variables in $F_t = [f_{1,t} \ ... \ f_{K,t}]^T$, exogenous (or pre-determined) to y_t'; $\overline{\gamma}_K^T = [\gamma_1 \ ... \ \gamma_K]$ is a vector of parameters to be calibrated, and $\xi_t \overset{i.i.d.}{\sim} N(0, S)$. The smoothing constants, λ_1 and λ_2, are transformations of the weights attached to the elements of the minimization problem (cyclical fluctuations, growth rate of the trend, and squared residuals of the economic relationship):

$$\min_{\{y_t^*\}_{t=1}^{T^*}} \sum_{t=1}^{T^*} \left\{ \frac{1}{\sigma_0^2} (y_t - y_t^*)^2 + \frac{1}{\sigma_1^2} \left(\Delta y_{t+1}^* - \Delta y_t^*\right)^2 + \frac{1}{\sigma_2^2} (\xi_t)^2 \right\}, \tag{A.3}$$

with $\lambda_1 = \frac{\sigma_0^2}{\sigma_1^2}$, $\lambda_2 = \frac{\sigma_0^2}{\sigma_2^2}$, $\sigma_0^2 = var\,(y_t - y_t^*)$, $\sigma_1^2 = var\left(\Delta y_{t+1}^* - \Delta y_t^*\right) = var\left(\Delta g_{t+1}^*\right)$, and $\sigma_2^2 = var\,(\xi_t) = S$. The state-space representation of the problem has

$$y_t = y_t^* + e_t \tag{A.4}$$

and $(A.2)$ as measurement equations. Equation $(A.4)$ relates actual output to its potential and $e_t \overset{i.i.d.}{\sim} N(0, C)$.[39] The transition equations, describing the evolution of the unobserved

[38] Laxton and Tetlow (1992).

[39] The implicit hypothesis that the output gap is white noise prevents the estimated, unobserved, variable (potential output) from *wandering away* too much from the observed variable (actual output). This hypothesis could be tested and compared to alternative assumptions, for example that the gap is persistent and is better represented as an autoregressive process. Such a possibility has been examined in the empirical literature. Modelling the gap as an autoregressive process may, perhaps, make more sense conceptually, but does not lead to significant differences in the estimated unobserved variables. The choice between the two alternatives should then be made depending on whether the unobserved variable is believed to be tightly linked to the observed variable, or whether economic shocks are thought to be persistent and able to open a gap for long periods.

variable, y_t^*, are

$$y_t^* = y_{t-1}^* + g_t^* + v_{1,t} \tag{A.5}$$

$$g_t^* = g_{t-1}^* + v_{2,t}, \tag{A.6}$$

with $v_t = \begin{pmatrix} v_{1,t} \\ v_{2,t} \end{pmatrix} = \begin{pmatrix} 0 \\ v_{2,t} \end{pmatrix} \overset{i.i.d.}{\sim} N(0, Q)$ and $Q = \begin{bmatrix} 0 & 0 \\ 0 & Q_2 \end{bmatrix}$. Equation $(A.5)$ is an identity; $(A.6)$ incorporates the hypothesis of persistence of potential output. $(A.5)$ and $(A.6)$ are representable in reduced form

$$\begin{pmatrix} y_t^* \\ g_t^* \end{pmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{pmatrix} y_{t-1}^* \\ g_{t-1}^* \end{pmatrix} + \begin{pmatrix} v_{2,t} \\ v_{2,t} \end{pmatrix}. \tag{A.7}$$

The simple economic relationship we use is a standard augmented Phillips curve[40]

$$\Delta\pi_t = \alpha\Delta\pi_{t-1} - \theta\left(y_t - y_t^*\right) + \delta q_{t-1} + \xi_t, \tag{A.8}$$

where $\pi_t = p_t - p_{t-1}$ is the inflation rate, q_t is a vector of temporary supply shocks. With quarterly data, $\Delta\pi_t = \pi_t - \pi_{t-1} \simeq [\log(P_t) - \log(P_{t-1})] - [\log(P_{t-1}) - \log(P_{t-2})]$, i.e., the variation of inflation from a quarter to another. We use the GDP deflator as price index. In this article, supply shocks are captured by the term $q_t = \frac{\epsilon_t - \epsilon_{t-1}}{\epsilon_{t-1}} \simeq [\log(\epsilon_t) - \log(\epsilon_{t-1})]$, where ϵ_t is the real effective exchange rate.

Combining $(A.4)$ and $(A.8)$, we get the reduced form

$$\begin{pmatrix} y_t \\ \Delta\pi_t \end{pmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \begin{pmatrix} y_t^* \\ g_t^* \end{pmatrix} + \begin{bmatrix} 0 & 0 \\ \alpha & \delta \end{bmatrix} \begin{pmatrix} \Delta\pi_{t-1} \\ q_{t-1} \end{pmatrix} + \begin{pmatrix} e_t' \\ \xi_t' \end{pmatrix} \tag{A.9}$$

[40] Ball and Moffitt (2001) estimate the US time-varying NAIRU in a two-step procedure. In the first step they estimate a Phillips curve under the assumption of constant NAIRU. We calibrate θ, α, and δ by running OLS on $\Delta\pi_t = \alpha\Delta\pi_{t-1} - \theta\left(y_t - y_t^*\right) + \delta q_{t-1} + \xi_t = \theta\left(\beta_0 + \beta_1 t\right) + \alpha\Delta\pi_{t-1} - \theta y_t + \delta q_{t-1} + \xi_t$ under an initial simplifying assumption of linear log potential output.

with $\begin{pmatrix} e'_t \\ \xi'_t \end{pmatrix} = \begin{bmatrix} 1 & 0 \\ -\theta & 1 \end{bmatrix} \begin{pmatrix} e_t \\ \xi_t \end{pmatrix} = u'_t \overset{i.i.d.}{\sim} N\left(0, \begin{bmatrix} C & -\theta C \\ -\theta C & \theta^2 C + S \end{bmatrix}\right)$. Transition equations have the same notation as in (A.7), with $\begin{pmatrix} v_{2,t} \\ v_{2,t} \end{pmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{pmatrix} 0 \\ v_{2,t} \end{pmatrix} = v'_t \overset{i.i.d.}{\sim}$ $N\left(0, \begin{bmatrix} Q_2 & Q_2 \\ Q_2 & Q_2 \end{bmatrix}\right)$.

We apply filter and smoother to the model[41]

$$Y_t = HX_t + GZ_t + u'_t \qquad (A.10)$$

$$X_{t+1} = AX_t + v'_{t+1} \qquad (A.11)$$

$$Y_t = \begin{pmatrix} y_t \\ \Delta\pi_t \end{pmatrix} \qquad X_t = \begin{pmatrix} y^*_t \\ g^*_t \end{pmatrix} \qquad Z_t = \begin{pmatrix} \Delta\pi_{t-1} \\ q_{t-1} \end{pmatrix}$$

$$H = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \qquad G = \begin{bmatrix} 0 & 0 \\ \alpha & \delta \end{bmatrix} \qquad A = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}$$

$$v'_{t+1} \overset{i.i.d.}{\sim} N\left(0, \begin{bmatrix} Q_2 & Q_2 \\ Q_2 & Q_2 \end{bmatrix}\right) \qquad u'_t \overset{i.i.d.}{\sim} N\left(0, \begin{bmatrix} C & -\theta C \\ -\theta C & \theta^2 C + S \end{bmatrix}\right)$$

$$\frac{C}{Q_2} = \frac{\sigma_0^2}{\sigma_1^2} = \lambda_1 = 1,600 \qquad \frac{C}{S} = \frac{\sigma_0^2}{\sigma_2^2} = \lambda_2 = 16.$$

If data on prices and supply shocks are not available, we use a univariate filter (HPUV) to

[41] If equation (A.4) was believed to be the true model, λ_1 and λ_2 could be estimated through maximum likelihood. The reason for applying the HP filter is the belief that output gaps are not just white noise. Thus, values for λ_1 and λ_2 are imposed rather than estimated. As Harvey and Jaeger (1993) suggest, from the standpoint of structural time series modeling, a multivariate HP filter is equivalent to the state-space model, (A.10) and (A.11), with the imposed structure.

θ and S can be estimated by OLS on (A.8). C and Q_2 follow given our choices of $\lambda_{1,2}$. The filtering/smoothing procedure is likely to be affected, at the beginning of the sample, by the choice of the initial conditions for the state variables. The filter stabilizes quickly, but it is crucial to initialize it properly so as not to get biased estimates at the beginning of the sample. Under conditions where C and Q are constant, both the estimation error covariance and the Kalman gain will converge quickly and then remain constant. These parameters can then be pre-computed by running the filter off-line. We propose this solution: a) we impose a prior initial estimate for the estimation error covariance (we set it equal to the identity matrix), and run the filter off-line; and b) we re-run the filter to get the filtered estimates for the unobserved variables after equalizing initial value of the estimation error covariance to the last observation (which should be close to its steady state) obtained in the previous recursion.

replicate the features of a standard HP filter. The sketched specification is preserved, except for the Phillips curve, which does not show up in the resulting state-space representation.[42]

Appendix B. Reliability of the Testing Strategy - Monte Carlo Experiments

Models sufficiently simple to replicate the same cross-correlation structure of original time series pairs and some of their most relevant features are a bivariate VAR for autocorrelated macroeconomic series and a bivariate normal for non-autocorrelated variables. We condition the DGP on the presence of a break. In a first set of experiments (Tables 6a and 6b), we choose the following representation for each pair of variables:

$$\begin{pmatrix} V_{A,t}^{1,2} \\ V_{B,t}^{1,2} \end{pmatrix} = \begin{pmatrix} c_A^{1,2} \\ c_B^{1,2} \end{pmatrix} + \sum_{i=1}^{h} F_i^{1,2} \begin{pmatrix} V_{A,t-i}^{1,2} \\ V_{B,t-i}^{1,2} \end{pmatrix} + \begin{pmatrix} \varepsilon_{A,t}^{1,2} \\ \varepsilon_{B,t}^{1,2} \end{pmatrix}, \quad \begin{pmatrix} \varepsilon_{A,t}^{1,2} \\ \varepsilon_{B,t}^{1,2} \end{pmatrix} \overset{i.i.d.}{\sim} N\left(0, \Omega^{1,2}\right),$$

here assumed to be the true data-generating process. Superscripts indicate the subsample over which the model is estimated.[43] We calibrate the DGP through estimation on real data. We let VAR coefficients and the covariance matrix of innovations vary between the two subsamples, that is, the correlation structure of artificial variables changes from one subsample to another.[44] The two estimated covariance matrices are assumed to be constant over their respective subsamples. We generate artificial data, apply candidate versions of bootstrap for the estimation of confidence intervals, and evaluate the goodness of the various resampling schemes following the six steps below. Of course, the ideal would be to attain estimated coverage probabilities that are close to the nominal level, α, and high estimated

[42] Initial conditions for the output gap are given in order to initialize the filter/smoother in all countries. These conditions correspond to potential output estimates taken from the OECD or from country-specific sources, depending on availability.

[43] Detrended macroeconomic series, as well as growth rates and structural shocks, are covariance stationary. A stationary $VAR(h)$ can generate stationary series with a cross-correlation structure similar to the original. The $VAR(h)$ representation – we use $h = 3, 4$ – is a compromise between a sufficiently parsimonious (given sample sizes) model and a model providing a good fit of macroeconomic data and eliminating most of the residuals' autocorrelation. To mimic independent and identically distributed data (structural shocks), we impose the restrictions $\left\{F_i^{1,2}\right\}_{i=1}^{h} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$, thus preserving the cross-correlation structure of the data when time series display no autocorrelation.

[44] When imposing the zero-restrictions on the matrices $\left\{F_i^{1,2}\right\}_{i=1}^{h}$, we let mean and covariance matrix of the resulting bivariate normal random vector, $\begin{pmatrix} V_{A,t} \\ V_{B,t} \end{pmatrix}$, change over the second subsample.

powers. We compare simulated sizes and powers to these ideals.

Step 1. We estimate $\left\{\widehat{F}_i^{1,2}\right\}_{i=1}^{h}$, $\widehat{c}_{A,B}^{1,2}$, and $\widehat{\Omega}^{1,2}$ by OLS from the original time series.

Step 2. Conditional on the estimated models (*true DGP*), we derive the *true* $\Delta\rho$ by randomly generating – 10,000 times – pairs of series driven by the DGP along the two subsamples of length Br and $(T-Br)$.[45] We make the cross-correlation structure of the two variables change from one sample to the other. We estimate correlation changes at each replication. The *true* $\Delta\rho$ is the average of the 10,000 random correlation changes.

Step 3. We create N^M quadruples of artificial series, $\left\{V_{A,s}^{1,m}\right\}_{s=1}^{Br}$, $\left\{V_{A,s}^{2,m}\right\}_{s=1}^{Br}$, $\left\{V_{B,s}^{1,m}\right\}_{s=Br+1}^{T}$, $\left\{V_{B,s}^{2,m}\right\}_{s=Br+1}^{T}$, for Monte Carlo analysis. We take the first h observations in the first subsample of original data as necessary starting values for the generation of artificial data through the estimated VARs. The last h observations in each first subsample of artificially-generated data are taken to produce the second artificial sample and rule out unnecessary *jumps*. Artificial datasets have the same length as the original.

Step 4. At each Monte Carlo replication, we compute confidence intervals for $\Delta\rho$ using the candidate bootstrap schemes we want to compare and the same number of bootstrap replications and iterations we selected for the applications.

Step 5. We calculate the proportion of α-level confidence intervals covering the *true* $\Delta\rho$ (estimated coverage probability).[46] The closer this proportion to the nominal coverage probability, the more reliable confidence intervals computed on original data. In an *ideal* setting, the estimated coverage probability should equal α.

Step 6. We compute the proportion of confidence intervals covering zero. This is the probability of not rejecting the null when it is false (conditional on the existence of a break in the correlation coefficient in correspondence of the Br^{th} observation). The *ideal* coverage

[45] All innovations are bivariate Gaussian, with a zero mean and variance-covariance matrix equal to $\widehat{\Omega}^{1,2}$.

[46] We use $N_O^B = 1,000$ bootstrap resamples (no iteration) for each of the $N^M = 1,000$ Monte Carlo replications. With iterated bootstraps, the nested bootstrap runs $N_O^B = 500$ times for each outer bootstrap replication and the number of Monte Carlo experiments, N^M, is at least 500. The higher N^M, the more precise the estimate for coverage probability.

should be zero. One minus this probability is an estimate for the statistical power of the test, given the level of the confidence interval and the bootstrap method used.[47] It is the probability of rejecting a false null. For a structural change in the correlation coefficient to be likely to be detected in the data, this probability should be large (ideally, it should equal one). The smaller the power, the bigger the chance of accepting the null if false.

Over the past twenty-five years or so, the volatility of macroeconomic aggregates has significantly fallen in most of the industrialized world. Timing and entity of such a decline vary with countries. The phenomenon is known in the literature as the Great Moderation.[48] Lower volatilities at some point in the sample would increase international correlations by definition (if the covariances are positive) and, in principle, may impact on the inference of our testing strategy. In a second set of Monte Carlo experiments (Table 6c) we take into account this potential feature of the data and assess the robustness of our econometrics to the new setting. To simulate the presence of the Great Moderation in the DGP and roughly match the select data, we estimate a unique VAR on the full sample:

$$\begin{pmatrix} V_{A,t} \\ V_{B,t} \end{pmatrix} = \begin{pmatrix} c_A \\ c_B \end{pmatrix} + \sum_{i=1}^{h} F_i \begin{pmatrix} V_{A,t-i} \\ V_{B,t-i} \end{pmatrix} + \begin{pmatrix} \varepsilon_{A,t} \\ \varepsilon_{B,t} \end{pmatrix}, \quad \begin{pmatrix} \varepsilon_{A,t} \\ \varepsilon_{B,t} \end{pmatrix} \overset{i.i.d.}{\sim} N(0, \Omega),$$

and let $\widehat{\Omega}$ change to $\widehat{\Omega}^{GM}$ at a chosen date in the first subsample. Namely, we let the variance terms in $\widehat{\Omega}$ fall by a factor $k_{GM} \in (0,1)$ – i.e., $\widehat{\Omega}^{GM}_{11,22} = k_{GM}\widehat{\Omega}_{11,22}$ and $\widehat{\Omega}^{GM}_{12} = \widehat{\Omega}^{GM}_{21} = \widehat{\Omega}_{12} = \widehat{\Omega}_{21}$, so that $\left|\widehat{\Omega}^{GM}\right| > 0$ – over the second part of the first subsample, after time $t_{GM} \in (1, Br)$; in the second subsample we decrease the covariance terms accordingly, so that conditional and unconditional correlations over the two subsamples remain unchanged.[49]

[47] The statistical power of the testing procedure is alternatively and equivalently defined as $\pi(H_1) = Prob(0 \notin I(\alpha;\Delta\rho)|H_1) = \{1 - Prob(0 \in I(\alpha;\Delta\rho)|H_1)\} = Prob(0 \notin I(\alpha;\Delta\rho)|\Delta\rho \neq 0) = \{1 - Prob(0 \in I(\alpha;\Delta\rho)|\Delta\rho \neq 0)\}$, where $I(\alpha;\Delta\rho)$ is a two-sided α-level confidence interval for $\Delta\rho$. We estimate $\pi(H_1)$ as $\widehat{\pi(H_1)} = \frac{\sum_{i=1}^{N^M} 1\{0 \notin I_i(\alpha;\Delta\rho)\}}{N^M}$.

[48] Past articles document recent moderation in output volatility in the US and in the other G7 economies (Doyle and Faust, 2002). Stock and Watson (2005) try to give explanations and shed some light on the origins of the phenomenon. Answers are not conclusive, yet, although possible causes might involve monetary policy, inventory management, and evolution of shocks.

[49] To the extent to which it is possible in a simplified framework, we check the robustness of the testing procedure, in terms of coverage, to changes in the variance-covariance matrix of the innovations in the DGP.

$\widehat{c}_{A,B}$ and $\{\widehat{F}_i\}_{i=1}^{h}$ do not vary. We use the steps above to estimate the coverage probabilities of confidence intervals under the null of no correlation variation after the break. Given the new set of assumptions in the DGP, we do not need to make use of step 2, since the *true* $\Delta\rho$ is zero by construction.

We simulate a *permanent* drop in the variability of random shocks, but leave the correlations unaltered between the two subsamples. We impose that the variances of the random shocks decrease at some point in the first subsample by a specified factor. The consequence is that the correlation coefficient goes up in the second part of the first subsample. This is done under the assumption that the conditional and unconditional correlation coefficients over the two subsamples stay the same. The covariance terms in the variance-covariance matrix are lowered in the second subsample, while the variances are kept at the lower level set in the second part of the first subsample. The conditional and unconditional correlation coefficients are thus increased in the second subsample and set equal to the conditional and unconditional correlation coefficients over the full first subsample. This Monte Carlo design under the null hypothesis is similar to that used by Doyle and Faust (2005).

8 Tables

COUNTRIES IN THE EUROPEAN UNION (1957) AND IN THE EUROPEAN ECONOMIC AND MONETARY UNION (01.01.1999)	
Belgium (BE)	*Ireland (IE)* [a]
Germany (DE)	*Greece (GR)* [b] [e]
France (FR)	*Spain (ES)* [c]
Italy (IT)	*Portugal (PT)* [c]
Luxembourg (LUX)	*Austria (AT)* [d]
Netherlands (NE)	*Finland (FI)* [d]

OTHER COUNTRIES IN THE EUROPEAN UNION AND CURRENT CURRENCY REGIMES	
Denmark (DK) [a]	Peg to the Euro through ERM II* (since 01.01.1999)
Sweden (SE) [d]	Managed Float (since 11.1992) - Not in ERM II*
United Kingdom (UK) [a]	Managed Float - Not in ERM II*

COUNTRIES IN THE NORTH AMERICAN FREE TRADE AGREEMENT (01.1994) AND CURRENT CURRENCY REGIMES	
Canada (CA) [f]	Managed Float/Floating Exchange Rate
Mexico (MEX)	Managed Float
USA (USA) [f]	Managed Float/Floating Exchange Rate

[a]In the European Union since 1973. [b]In the European Union since 1981. [c]In the European Union since 1986. [d]In the European Union since 1995. [e]In the European Economic and Monetary Union since 01.01.2001. [f]In the Canada-US Free Trade Agreement since 01.1989.

*European Exchange Rate Mechanism II

Table 1. List of Countries

EU15 - Detrended Real GDP - HPMV (KF)

	AT	BE	DE	DK	ES	FI	FR	GR	IT	NE	SE	UK
AT	---											
BE	0.593	---										
DE	0.346	0.307	---									
DK	**1.368**	**0.794**	0.128	---								
ES	0.450	0.098	**0.653**	0.322	---							
FI	**1.333**	0.328	0.827	**0.643**	0.099	---						
FR	0.256	0.072	0.691	0.574	0.216	0.180	---					
GR	-0.346	-0.126	0.089	-0.380	-0.081	-0.208	0.236	---				
IT	0.364	-0.119	**0.578**	0.267	0.105	0.068	0.197	0.179	---			
NE	**0.529**	0.398	**0.695**	**0.641**	0.158	**0.528**	0.360	-0.422	0.077	---		
SE	0.293	0.162	**0.607**	**0.721**	0.032	0.167	0.185	-0.406	-0.229	0.309	---	
UK	**1.319**	**0.667**	0.547	-0.120	0.080	0.051	**0.646**	-0.086	0.197	0.336	0.615	---

		UP	Sign. UP	DOWN	Sign. DOWN	Total
EU15	**#**	40	**15**	11	**0**	66
	%	60.6%	**22.7%**	16.7%	**0.0%**	100.0%
EMU12	**#**	25	**6**	5	**0**	36
	%	69.4%	**16.7%**	13.9%	**0.0%**	100.0%

Samples (Quarterly Data). AT: 1988.4-2006.3; BE: 1980.4-2006.3; DE: 1991.4-2006.3; DK: 1977.4-2006.3; ES: 1980.4-2006.3; FI: 1975.4-2006.3; FR: 1978.4-2006.3; GR: 1975.4-2006.2; IT: 1980.4-2006.3; NE: 1977.4-2006.3; SE: 1993.4-2006.3; UK: 1975.4-2006.3.
Breakpoint Date: 1998.4.

EU15 - Real GDP - Growth

	AT	BE	DE	DK	ES	FI	FR	GR	IT	NE	SE	UK
AT	---											
BE	0.118	---										
DE	0.148	-0.024	---									
DK	**0.506**	0.005	0.035	---								
ES	0.015	-0.322	-0.006	0.089	---							
FI	0.256	0.235	0.191	-0.067	0.090	---						
FR	-0.268	0.034	0.055	0.102	0.075	-0.057	---					
GR	-0.053	**-0.388**	-0.263	-0.121	-0.246	0.032	-0.188	---				
IT	-0.071	0.189	**0.525**	0.135	0.242	0.270	0.217	-0.241	---			
NE	**0.314**	0.086	0.099	**0.359**	-0.049	0.092	0.278	-0.186	**0.444**	---		
SE	**0.369**	0.162	**0.650**	0.489	-0.229	0.220	-0.095	-0.270	-0.198	**0.534**	---	
UK	0.308	0.125	0.182	-0.063	0.238	-0.104	**0.306**	-0.098	**0.411**	-0.123	0.124	---

		UP	Sign. UP	DOWN	Sign. DOWN	Total
EU15	**#**	32	**10**	23	**1**	66
	%	48.5%	**15.2%**	34.8%	**1.5%**	100.0%
EMU12	**#**	19	**3**	13	**1**	36
	%	52.8%	**8.3%**	36.1%	**2.8%**	100.0%

Samples (Quarterly Data). ***Real GDP*** . AT: 1988.2-2006.3; BE: 1980.2-2006.3; DE: 1991.2-2006.3; DK: 1977.2-2006.3; ES: 1980.2-2006.3; FI: 1975.2-2006.3; FR: 1978.2-2006.3; GR: 1975.2-2006.2; IT: 1980.2-2006.3; NE: 1977.2-2006.3; SE: 1993.2-2006.3; UK: 1975.2-2006.3.
Breakpoint Date: 1998.4.

Symbols and Notation. **Correlation Changes in bold**: significant at either 5% or 10% level. #: number of observations; %: proportion out of total number of entries; **UP**: number of non-significantly positive correlation changes; **Sign. UP**: number of significantly positive correlation changes; **DOWN**: number of non-significantly negative correlation changes; **Sign. DOWN**: number of significantly negative correlation changes.

Table 2. EU15 - GDP, HPMV (Kalman Filter) and Growth Rates - Pairwise Correlation Changes

EU15 - Detrended Final Consumption Expenditure - HP

	AT	BE	DE	DK	ES	FI	FR	GR	IT	NE	SE	UK
AT	---											
BE	0.077	---										
DE	0.072	0.264	---									
DK	0.272	-0.343	-0.106	---								
ES	0.385	-0.140	0.317	0.600	---							
FI	0.021	**-0.564**	0.140	0.221	**-0.576**	---						
FR	0.173	0.151	0.028	-0.025	0.071	**-0.626**	---					
GR	0.009	-0.009	-0.088	0.140	-0.186	**-0.628**	0.149	---				
IT	0.117	0.033	0.550	0.020	-0.088	-0.087	0.034	**-0.275**	---			
NE	0.043	0.282	**0.641**	-0.478	-0.107	-0.104	0.116	-0.343	0.481	---		
SE	**0.769**	**1.069**	0.455	0.417	**0.892**	**1.114**	0.095	0.318	**0.702**	0.254	---	
UK	0.502	0.284	0.146	-0.403	0.039	**-0.621**	0.313	-0.092	0.259	-0.351	0.364	---

		UP	Sign. UP	DOWN	Sign. DOWN	Total
EU15	**#**	38	**6**	16	**6**	66
	%	57.6%	**9.1%**	24.2%	**9.1%**	100.0%
EMU12	**#**	21	**1**	9	**5**	36
	%	58.3%	**2.8%**	25.0%	**13.9%**	100.0%

Samples (Quarterly Data). ***Final Consumption Expenditure*** . AT: 1988.1-2007.1; BE: 1980.1-2007.1; DE: 1991.1-2007.1; DK: 1977.1-2007.1; ES: 1980.1-2007.1; FI: 1975.1-2007.1; FR: 1978.1-2007.1; GR: 1975.1-2006.2; IT: 1980.1-2007.1; NE: 1977.1-2007.1; SE: 1993.1-2007.1; UK: 1975.1-2007.1.
Breakpoint Date: 1998.4.

EU15 - Detrended Gross Fixed Capital Formation - HP

	AT	BE	DE	DK	ES	FI	FR	GR	IT	NE	SE	UK
AT	---											
BE	0.294	---										
DE	**0.292**	0.579	---									
DK	**0.926**	0.368	**0.463**	---								
ES	0.432	0.097	**0.445**	0.396	---							
FI	**0.850**	-0.053	**0.824**	0.459	-0.010	---						
FR	0.335	0.018	**0.340**	**0.585**	-0.058	0.172	---					
GR	**0.339**	-0.401	0.164	-0.286	-0.138	-0.029	-0.124	---				
IT	-0.116	-0.387	-0.114	0.111	**-0.649**	-0.636	-0.466	-0.329	---			
NE	**0.655**	0.277	**0.455**	**0.364**	**0.584**	**0.549**	**0.531**	**-0.302**	-0.305	---		
SE	0.553	**1.266**	0.651	0.621	0.391	0.765	0.019	-0.075	-0.298	**1.018**	---	
UK	0.217	-0.074	0.387	-0.170	0.269	-0.012	0.083	-0.049	0.083	0.254	**0.581**	---

		UP	Sign. UP	DOWN	Sign. DOWN	Total
EU15	**#**	25	**18**	21	**2**	66
	%	37.9%	**27.3%**	31.8%	**3.0%**	100.0%
EMU12	**#**	9	**11**	14	**2**	36
	%	25.0%	**30.6%**	38.9%	**5.6%**	100.0%

Samples (Quarterly Data). ***Gross Capital Formation*** . AT: 1988.1-2006.3; BE: 1980.1-2006.2; DE: 1991.1-2006.3; DK: 1977.1-2006.3; ES: 1980.1-2006.3; FI: 1975.1-2006.2; FR: 1978.1-2006.3; GR: 1975.1-2006.2; IT: 1980.1-2006.3; NE: 1977.1-2006.3; SE: 1993.1-2006.3; UK: 1975.1-2006.3.
Breakpoint Date: 1998.4.

Symbols and Notation. **Correlation Changes in bold**: significant at either 5% or 10% level. #: number of observations; %: proportion out of total number of entries; **UP**: number of non-significantly positive correlation changes; **Sign. UP**: number of significantly positive correlation changes; **DOWN**: number of non-significantly negative correlation changes; **Sign. DOWN**: number of significantly negative correlation changes.

Table 3. EU15 - Final Consumption Expenditure and Gross Fixed Capital Formation, HP Filter - Pairwise Correlation Changes

EU15 - Detrended Trade Activity - HP

	AT	BE	DE	DK	ES	FI	FR	GR	IT	NE	SE	UK
AT	---											
BE	0.210	---										
DE	-0.012	0.164	---									
DK	0.217	0.150	0.125	---								
ES	0.083	0.457	-0.058	0.277	---							
FI	**0.804**	0.376	**0.936**	**0.661**	**0.516**	---						
FR	0.099	0.095	0.066	**0.290**	0.106	**0.558**	---					
GR	0.461	**0.848**	0.145	0.081	**0.498**	**0.535**	0.381	---				
IT	0.217	0.301	0.264	0.246	0.261	**0.413**	**0.207**	0.313	---			
NE	**0.331**	**0.539**	0.033	0.180	0.403	**0.831**	**0.340**	**0.493**	0.372	---		
SE	0.126	0.099	0.231	0.027	0.209	0.073	-0.083	**0.691**	0.063	0.157	---	
UK	0.490	0.014	0.666	**0.476**	0.265	0.259	**0.388**	0.231	0.146	0.341	0.477	---

		UP	Sign. UP	DOWN	Sign. DOWN	Total
EU15	**#**	44	**19**	3	**0**	66
	%	66.7%	**28.8%**	4.5%	**0.0%**	100.0%
EMU12	**#**	20	**14**	2	**0**	36
	%	55.6%	**38.9%**	5.6%	**0.0%**	100.0%

Samples (Quarterly Data). ***Trade Activity*** . AT: 1988.1-2006.3; BE: 1980.1-2006.3; DE: 1991.1-2006.3; DK: 1977.1-2006.3; ES: 1980.1-2006.3; FI: 1975.1-2006.3; FR: 1978.1-2006.3; GR: 1975.1-2006.2; IT: 1980.1-2006.3; NE: 1977.1-2006.3; SE: 1993.1-2006.3; UK: 1975.1-2006.3.

Breakpoint Date: 1998.4.

EU15 - Stock Market Index - Monthly Return

	AT	BE	DE	DK	ES	FI	FR	GR	IE	IT	NE	PT	UK
AT	---												
BE	-0.062	---											
DE	**-0.246**	-0.165	---										
DK	-0.180	-0.036	0.065	---									
ES	-0.148	-0.206	**0.116**	-0.050	---								
FI	**-0.354**	**-0.372**	0.140	-0.179	0.014	---							
FR	-0.194	-0.194	**0.111**	0.150	0.094	**0.249**	---						
GR	-0.185	-0.159	-0.038	-0.192	-0.031	-0.003	0.012	---					
IE	-0.065	-0.143	0.083	-0.122	-0.160	**-0.235**	-0.050	-0.123	---				
IT	**-0.371**	-0.227	0.143	-0.133	-0.017	-0.051	**0.128**	-0.203	-0.172	---			
NE	-0.104	-0.117	0.098	0.056	0.021	0.055	**0.099**	-0.011	-0.026	0.035	---		
PT	**-0.474**	-0.244	0.046	-0.100	0.027	0.017	0.004	-0.273	-0.263	-0.009	-0.133	---	
UK	0.046	0.005	**0.309**	0.012	0.022	0.098	0.120	0.010	-0.074	0.073	**0.187**	-0.150	---

		UP	Sign. UP	DOWN	Sign. DOWN	Total
EU15	**#**	25	**7**	40	**6**	78
	%	32.1%	**9.0%**	51.3%	**7.7%**	100.0%
EMU12	**#**	14	**5**	30	**6**	55
	%	25.5%	**9.1%**	54.5%	**10.9%**	100.0%

Samples (Monthly Data). ***Stock Market Index (Returns)*** . AT: 1986.2-2006.11; BE: 1990.2-2006.11; DE: 1974.7-2006.11; DK: 1990.1-2006.11; ES: 1987.2-2006.11; FI: 1987.2-2006.11; FR: 1987.8-2006.11; GR: 1988.10-2006.11; IE: 1983.2-2006.11; IT: 1994.11-2006.11; NE: 1983.2-2006.11; PT: 1993.1-2006.11; UK: 1978.2-2006.11.

Breakpoint Date: 1998.12.

Symbols and Notation. **Correlation Changes in bold**: significant at either 5% or 10% level. #: number of observations; %: proportion out of total number of entries; **UP**: number of non-significantly positive correlation changes; **Sign. UP**: number of significantly positive correlation changes; **DOWN**: number of non-significantly negative correlation changes; **Sign. DOWN**: number of significantly negative correlation changes.

Table 4. EU15 - Trade Activity (HP Filter) and Stock Market Index (Returns) - Pairwise Correlation Changes

Business Cycle Measure	Filtering Method	CA-MEX	CA-USA	MEX-USA
Real GDP	HPMV (KF)	0.085	-0.164	**0.566**
	Growth	**-0.169**	-0.237	0.140
Final Consumption Expenditure	HP	**0.730**	0.043	**0.965**
Gross Fixed Capital Formation	HP	**0.485**	0.103	0.239
Stock Market Index	Return[a]	**0.328**	-0.064	-0.114
Trade Activity	HP	0.050	-0.023	0.046

Samples (Quarterly Data). ***Real GDP*** . CA: 1980.1-2006.3; MEX: 1980.1-2006.3 (from 1980.2 in Real GDP Growth Rates, from 1980.4 in HPMV); USA: 1974.2-2006.3. ***Final Consumption Expenditure*** . CA: 1980.1-2006.4; MEX: 1980.1-2006.4; USA: 1980.1-2006.4. ***Gross Fixed Capital Formation*** . CA: 1980.1-2006.4; MEX: 1980.1-2006.4; USA: 1980.1-2006.4. ***Trade Activity*** . CA: 1981.1-2006.3; MEX: 1980.1-2006.3; USA: 1981.1-2006.3.
Samples (Monthly Data). ***Stock Market Index (Returns)*** . CA: 1982.2-2006.11; MEX: 1983.2-2006.11; USA: 1982.2-2006.11.
Breakpoint Date (Quarterly Data): 1993.4. **Breakpoint Date (Monthly Data)**: 1993.12.
[a]Monthly Data.
Symbols and Notation. **Correlation Changes in bold**: significant at either 5% or 10% level.

Table 5. NAFTA - Pairwise Correlation Changes

	Simulated Data		Monte Carlo Experiment			
Bootstrap Type	**"True" Statistics**		**Coverage Probability**		**Statistical Power**	
Resampling Scheme	Correlations		Percentile CI		Percentile CI	
	First Sample	*Change*	*90%*	*95%*	*90%*	*95%*
			EXPERIMENT 1			
NOB	-0.48	**1.36**	71.6%	81.4%	100.0%	100.0%
OB	-0.48	**1.37**	74.8%	83.3%	99.5%	99.3%
Stationary	-0.48	**1.37**	77.0%	84.3%	99.7%	99.7%
Iterated - OB	-0.48	**1.37**	87.6%	93.6%	96.4%	94.2%
Iterated - Stationary	-0.48	**1.36**	86.7%	94.0%	98.7%	98.3%
Iterated - Parametric	-0.48	**1.36**	98.9%	99.1%	98.6%	98.6%
			EXPERIMENT 2			
NOB	-0.39	**1.31**	79.9%	85.6%	99.9%	99.9%
OB	-0.39	**1.31**	89.3%	93.0%	99.9%	99.7%
Stationary	-0.39	**1.31**	88.6%	93.4%	100.0%	100.0%
Iterated - OB	-0.39	**1.31**	96.4%	98.0%	98.0%	97.0%
Iterated - Stationary	-0.39	**1.31**	93.3%	97.0%	99.9%	99.3%
Iterated - Parametric	-0.39	**1.31**	90.7%	95.1%	99.6%	99.1%
			EXPERIMENT 3			
NOB	0.12	**0.64**	77.0%	84.1%	87.1%	82.1%
OB	0.12	**0.64**	79.6%	87.8%	85.4%	76.9%
Stationary	0.11	**0.64**	79.0%	86.2%	87.2%	82.9%
Iterated - OB	0.12	**0.64**	88.4%	94.8%	69.2%	55.4%
Iterated - Stationary	0.12	**0.64**	87.9%	92.3%	76.0%	63.4%
Iterated - Parametric	0.12	**0.64**	92.1%	97.1%	78.3%	69.4%
			EXPERIMENT 4			
NOB	0.40	**0.42**	83.6%	89.5%	73.4%	63.4%
OB	0.40	**0.42**	80.1%	87.9%	61.4%	50.5%
Stationary	0.40	**0.42**	85.4%	90.7%	73.6%	63.0%
Iterated - OB	0.40	**0.42**	93.6%	96.4%	34.6%	24.4%
Iterated - Stationary	0.40	**0.42**	91.6%	95.4%	55.0%	40.7%
Iterated - Parametric	0.40	**0.42**	94.6%	97.6%	63.1%	48.1%

DGPs are calibrated by estimating corresponding models on real data
Experiment 1: output gaps (KF) - Austria and Denmark - DGP: VAR(4)
Experiment 2: output gaps (KF) - Austria and Finland - DGP: VAR(3)
Experiment 3: output gaps (KF) - France and UK - DGP: VAR(3)
Experiment 4: output gaps (KF) - Belgium and Netherlands - DGP: VAR(4)

Bootstrap Type - Resampling Scheme
NOB: Non-Overlapping Blocks (Fixed Length)
OB: Overlapping Blocks (Fixed Length)
Stationary: Overlapping Blocks (Random Length)
Parametric: Model-Based (Correct Specification)

Coverage Probability and Statistical Power
Percentile CI: Percentile Confidence Interval

Notes: This table reports the results of four different Monte Carlo experiments. We use 10000 replications to estimate the "true" statistics in the simulated data through the indicated DGP; 1000 Monte Carlo replications to estimate empirical coverage probabilities and statistical powers when the bootstrap type is NOB, OB, and Stationary. With Iterated - OB we run 500 Monte Carlo replications, 700 with Iterated - Stationary. The length of the first subsample is 41 in Experiments 1 and 2, 81 in Experiment 3, 73 in Experiment 4. The length of the second subsample is 31 in all the experiments. All innovations are independent and identically distributed as bivariate normals.

Table 6a. Monte Carlo Experiments (1)

Bootstrap Type	**Simulated Data**		**Monte Carlo Experiment**											
	"True" Statistics		**Coverage Probability**						**Statistical Power**					
Resampling Scheme	Correlations		Percentile CI		BCa CI		BC CI		Percentile CI		BCa CI		BC CI	
	First Sample	*Change*	*90%*	*95%*	*90%*	*95%*	*90%*	*95%*	*90%*	*95%*	*90%*	*95%*	*90%*	*95%*
					EXPERIMENT 5									
SI	0.12	**-0.35**	89.1%	93.3%	89.0%	93.2%	89.0%	93.4%	52.4%	39.5%	51.9%	41.3%	51.7%	40.0%
Iterated - SI	0.12	**-0.35**	88.9%	94.0%	---	---	---	---	49.0%	36.3%	---	---	---	---
					EXPERIMENT 6									
SI	0.02	**0.33**	87.7%	93.4%	87.6%	92.9%	87.7%	92.9%	50.5%	39.5%	49.7%	39.1%	49.7%	38.7%
Iterated - SI	0.02	**0.33**	89.1%	94.3%	---	---	---	---	46.0%	34.0%	---	---	---	---
					EXPERIMENT 7									
SI	0.08	**-0.69**	89.5%	95.0%	88.9%	93.7%	88.9%	94.0%	97.2%	94.8%	97.3%	94.7%	97.1%	94.7%
Iterated - SI	0.08	**-0.69**	91.4%	96.1%	---	---	---	---	96.1%	92.1%	---	---	---	---
					EXPERIMENT 8									
SI	0.22	**-0.46**	88.6%	93.9%	88.6%	94.1%	88.4%	94.3%	51.1%	39.8%	51.9%	39.9%	51.8%	39.4%
Iterated - SI	0.21	**-0.46**	91.6%	96.0%	---	---	---	---	45.3%	33.3%	---	---	---	---

DGPs are calibrated by estimating corresponding models on real data
Experiment 5: shock1 - Denmark and Finland - DGP: VAR(0)
Experiment 6: shock2 - Denmark and Italy - DGP: VAR(0)
Experiment 7: shock3 - Belgium and Finland - DGP: VAR(0)
Experiment 8: shock1 - Germany and Spain - DGP: VAR(0)

Coverage Probability and Statistical Power
Percentile CI: Percentile Confidence Interval
BCa CI: Bias-Corrected and Accelerated Confidence Interval
BC CI: Bias-Corrected Confidence Interval

Bootstrap Type - Resampling Scheme
SI: Standard Independent

Notes: This table reports the results of four different Monte Carlo experiments. We use 10000 replications to estimate the "true" statistics in the simulated data through the indicated DGP; 1000 Monte Carlo replications to estimate empirical coverage probabilities and statistical powers when the bootstrap type is SI. With Iterated - SI we run 700 Monte Carlo replications. The length of the first subsample is 71 in Experiments 5 and 7, 70 in Experiment 6, and 20 in Experiment 8. The length of the second subsample is 31 in all the experiments. All innovations are independent and identically distributed as bivariate normals.

Table 6b. Monte Carlo Experiments (2)

	Great Moderation Parameters		Monte Carlo Experiment Coverage Probability	
Bootstrap Type				
Resampling Scheme	K_{GM}	t_{GM}	Percentile CI	
			90%	*95%*
	EXPERIMENT 9			
Iterated - Stationary	0.48	33	88.1%	94.0%
Iterated - Parametric	0.48	33	90.4%	94.9%
	EXPERIMENT 10			
Iterated - Stationary	0.48	20	91.0%	95.6%
Iterated - Parametric	0.48	20	91.9%	96.4%
	EXPERIMENT 11			
Iterated - Stationary	0.55	18	88.1%	93.1%
Iterated - Parametric	0.55	18	88.9%	94.3%

DGPs are calibrated by estimating corresponding models on real data
Experiment 9: output gaps (KS) - Canada and USA - DGP: VAR(4)
Experiment 10: output gaps (KS) - Canada and USA - DGP: VAR(4)
Experiment 11: output gaps (KS) - France and Italy - DGP: VAR(3)

Bootstrap Type - Resampling Scheme
Stationary: Overlapping Blocks (Random Length)
Parametric: Model-Based (Correct Specification)

Coverage Probability
Percentile CI: Percentile Confidence Interval

Notes: This table reports the results of three different Monte Carlo experiments simulating the presence of the Great Moderation in the business cycle data. We run 700 Monte Carlo replications to estimate empirical coverage probabilities. The length of the first subsample is 56 in Experiments 9 and 10, 73 in Experiment 11. The length of the second subsample is 51 in Experiments 9 and 10, 31 in Experiment 11. All innovations are independent and identically distributed as bivariate normals. Innovation variances are scaled down by a factor K_{GM} at the date of occurrence of the Great Moderation (in the table, it is indicated as t_{GM}); covariance terms are scaled down accordingly at the beginning of the second subsample so that conditional and unconditional correlations remain unchanged from the first sample to the second sample. VAR coefficients stay constant over the whole sample.

Table 6c. Monte Carlo Experiments (3)