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. Especially for some specific subgroups of countries, we find evidence of higher correlations in Europe following the creation of the EMU in 1999. We detect more pronounced correlations at least between Mexico and the US in North America after the enforcement of the NAFTA in 1994. We do not, however, find rising synchronization between Hong Kong and the US pursuant to the introduction of a linked exchange rate system – still in effect today – at the end of 1983. Results are derived from an econometric framework based on nonparametric iterated stationary bootstrap methods, whose statistical reliability and performance we carefully assess.

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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://pierangelo.depace.googlepages.com`.

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. So far, however, empirical evidence has been mixed.[1]

In this work we 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 and focus on where breaks are most likely. We restrict our attention to three major transformations of monetary and trade regimes: the birth of the European Economic and Monetary Union (EMU) in January 1999, the enforcement of the North American Free Trade Agreement (NAFTA) in January 1994, and the introduction of a linked exchange rate system between the Hong Kong dollar and the US dollar in October 1983.[2] Inspired by theoretical considerations, we statistically test whether such shifts represent structural breaks in international comovement.[3] Second, we analyze measures of trade and financial integration – as well as output and other real variables as in standard empirical literature – to assess magnitude and nature of convergence (or divergence) across countries. To shed light on the characteristics of international integration, we examine how the comovement of potential determinants of business cycle synchronization has mutated following the aforementioned events.[4] Third, we study the small-sample inference probabilities of the econometric devices we construct for the specific statistical question

[1] See, for example, Coe and Helpman (1995), Frankel and Rose (1998), De Grauwe and Mongelli (2005).

[2] A linked exchange rate system is an exchange rate regime that links the exchange rate of a currency to another. Unlike a fixed exchange rate system, the central bank of the country that adopts the system does not interfere in the foreign exchange market by controlling supply and demand of the currency to influence the exchange rate. Instead, the exchange rate is stabilized by a mechanism.

[3] We also consider the case of the Canada-United States Free Trade Agreement (CUSFTA) in January 1989.

[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.

we intend to answer. Problems with inference on comovement changes are well-known; Doyle and Faust (2005) explain in detail why testing for them is generally difficult. We adopt sensible techniques, different from previous studies on the subject, compare them with alternative approaches within the same class, and, as a methodological contribution, provide evidence of their good statistical properties (coverage and power) through Monte Carlo experiments.

In most empirical work, authors do not test for the statistical significance of comovement variations and merely stress the presence of higher or lower levels of synchronization across countries and over time without much attention to the uncertainty surrounding point estimates. Among the few who test, the evidence is heterogeneous. Doyle and Faust (2005) use formal statistical methods to test for changes in measures of international business cycle comovement. They apply parametric bootstrap techniques to output, consumption, and investment in G7 countries, but are not able to detect systematic statistically significant synchronization modifications. Through statistical tests based on a factor-structural vector autoregression ($FSVAR$), Stock and Watson (2005) describe (i) the emergence of two groups of economies – Euro-area countries and English-speaking countries – characterized by synchronous cycles; and (ii) the declining volatility of common G7 shocks. In the present paper we build upon this literature and devote great care to the econometrics to be used for correct inference on synchronization variations.

Specifically, we propose tools to analyze pairwise cycle synchronization between countries and joint comovement for groups of them. 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 correlation coefficients of stationary business cycle time series following an exogenous date.[5] We apply nonparametric bootstrap methods to the data to generate the testing procedure for the detection of statistically significant correlation variations and to solve common problems associated with the study of macroeconomic series.[6] The nonparametric approach allows us to analyze at once an ex-

[5] Consistently with much literature on Optimum Currency Areas, assessing degree of economic openness and symmetry of incomes and other macroeconomic variables is crucial for understanding the net benefits from economic integration.

[6] As we explain below, we resort to an iterated version of Politis and Romano (1994b)'s stationary bootstrap.

tended set of economies including industrialized countries in the European Union (EU) and North America and newly industrialized countries (Mexico and Hong Kong). Subject to data availability, we focus on pairwise and joint interrelations among up to nineteen economies and employ a broad range of variables for estimation of and inference on select cycle measures and for close examination of the degree of international economic and financial integration, which might ultimately influence synchronization. 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. Nonetheless, extensive Monte Carlo experiments show that (i) our ability to identify significant correlation switches is substantial, (ii) the testing strategy is accurate, and (iii) our approach is a structure within which dealing with short time series is possible and does not vitiate inference reliability.[7]

Based on econometric evidence, we conclude that comovement has moderately increased in Europe since the birth of the EMU in terms of real economic activity. Stronger correlations have prevailed in specific subgroups of countries, among which the so-called Deutsche Marc (DM) Bloc and core EU. These higher levels of comovement have been accompanied by more synchronized financial markets among core EU/EMU countries – whereas non-core countries (particularly Austria and Belgium) have become more isolated – and by significantly more correlated trade volumes across Europe.[8] Taken as a whole, the NAFTA area has not experienced significant comovement changes since 1994, but we are able to detect higher pairwise correlations at least between Mexico and the US, and some significant increases between Mexico and Canada as for a few variables other than output (consumption, investment, and stock market returns). Output growth rates are significantly less synchronized between Canada and Mexico. With some caveats, we support the view that economic and financial integration came with (possibly led to) higher levels of macroeconomic synchronization at least in the European Union, to some extent in North America. On the other hand, we are not able to estimate significant correlation increases between the USA and Hong Kong after

[7] As we describe later in the case of autocorrelated stationary series, for example, 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.

[8] We define trade volume (or trade activity) as imports plus exports.

the introduction of the linked exchange rate system between their currencies in 1983.

2 The Econometric Framework: Estimation and Inference

We construct a testing strategy based on the application of the iterated (double) stationary bootstrap, a nonparametric version of bootstrap. Within the existing literature on business cycles, this represents a viable solution to attenuate the effects of the drawbacks that may arise in small samples. The framework is particularly effective in the case of Europe, for which long series are not always existent and only eight years of data can be used to describe the changes that have occurred since the birth of the monetary union. The technique also allows us to study a larger set of countries and variables than previous articles. We assess validity, accuracy, and power of the proposed approach in a number of situations through proper Monte Carlo simulations.

We extract economic cycles from the data and test for the significance of correlation changes in correspondence of exogenous dates.[9] The initial focus is on country-specific measures of real output. Most studies estimate business cycles through the application of the Hodrick-Prescott (HP) filter or the Band-Pass (BP) filter on the log-levels of the data. In this paper, we treat real output much more carefully and provide several estimates for the output gap to better appraise the robustness of our inference and conclusions. First, we refer to Harvey (1985), Harvey and Jaeger (1993), and Boone (2000) and use semi-structural methods for output gap estimation based on the application of the Kalman filter/smoother (KF/KS) in a suitable state-space model. Second, we employ macroeconomic filters conditional on an appropriate macroeconomic production function to obtain cyclical components from output series. Finally, we use structural vector autoregressions ($SVAR$) and a set of long-run restrictions to decompose the variance of vectors of economic variables and derive structural supply and demand shocks. Only with variables other than real GDP, we use the

[9] In principle, we should not use series in levels or log-levels. If we did, long-term correlations would dominate business cycle correlations. On the other hand, by taking growth rates by first-differencing the logs, correlations would be dominated by the short-term noise. We then need to use filters to extract information on the short-term movements (and comovements) of the series. Filters, of course, do have effects on the shape of cycles and on the features of comovement across economies.

model-free standard univariate HP filter if detrending is needed to capture business cycle comovements.

2.1 A Strategy to Test for Comovement Changes

As mentioned, we define economic cycle comovement as the unconditional correlation coefficient between two series describing the same cycle measure for two different countries.[10] Let T be the length of the common sample for those two series, $Br \in (1, T)$ the length of the first subsample, and ρ_2 and ρ_1 their correlation coefficients over $[Br + 1, T]$ and $[1, Br]$. Testing whether Br is a significant breakpoint in international business cycle synchronization is equivalent to testing whether the pairwise correlation change (PCC), $\Delta\rho = (\rho_2 - \rho_1)$, is statistically significant. Formally, we consider 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. Conventional asymptotics fails with time-dependent autocorrelated data and, with the relatively small sample sizes available in macroeconomic applications, often gives poor approximations to the distributions of estimators and test statistics.[11] The obvious 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 for the evaluation

[10] The unconditional correlation coefficient between two variables is a measure of the strength of their linear relationship and of the intensity of their symmetry, an estimate of the precision of relation between them. A problem with the use of this statistic is that a high value may be the result of significant comovement through time, or the result of a single large shock common to the two series. Unlike covariances, which measure dispersion and the common variability between two variables, correlation coefficients (and their changes) measure association, are dimensionless (i.e., they are independent of the units in which the two variables are expressed), scaled, bounded, and immediately comparable. 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.

[11] See Fisher (1915) and (1921), Gayen (1951), Hotelling (1953), and Hawkins (1989) for the case of 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.

of the distribution of interest. 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.[12]

One of the issues to be solved regards the choice of the resampling scheme for the application of the bootstrap and the estimation of the sampling distribution of the estimator of interest. 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 correlation coefficients over two contiguous subsamples and base our inference on the construction of two-sided α-level confidence intervals from the resulting bootstrap distribution. We can thus test for significant breaks and infer the direction of the shift. We set values for α to the conventional 0.90 or 0.95 and hold rejections of the null in 10% or 5% level tests as a sign of parameter instability. We apply same logic and techniques to a global index of comovement changes for groups of countries and test for its statistical significance over various samples. In the next sections we motivate and describe thoroughly our econometric choices.

Estimating Sampling Distributions via Bootstrap

There are essentially two approaches to resampling in the time domain. The first approach is parametric, or model-based, whose idea is to fit a model to the data to obtain non-autocorrelated residuals and then to generate new series by incorporating random samples from the residuals into the fitted model. The second approach is nonparametric, which treats as exchangeable not innovations, but blocks of consecutive observations of original data. In both cases, the bootstrap distribution of a statistic is obtained by collecting the values of that statistic computed at each bootstrap resample. The nonparametric bootstrap makes weak assumptions on the structure of the data-generating process (DGP) and generates errors in the

[12] Horowitz (2001).

rejection probability of statistical tests and in the coverage probability of confidence intervals that converge to zero faster than in the case of first-order asymptotic approximations. Faster convergence rates – i.e., higher orders of asymptotic refinement – are achievable through the imposition of additional structure on the DGP, as in the parametric bootstrap. However, these faster rates may come at a cost: if the finite-dimensional parametric model that reduces the DGP to independent random sampling in the parametric bootstrap is misspecified, estimators may turn out inconsistent and inference unreliable.[13]

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.[14] Heuristically, block length should equal the shortest lag at which autocorrelations become negligible.

[13]Parametric methods require assumptions on the marginal probability distributions of the variables used and on the spatial and temporal covariance structure of those variables; nonparametric methods directly retain the empirical structure of the observed variables. Parametric methods require estimates of model parameters, which nonparametric methods can either minimize or avoid completely. Parametric methods make business cycle analysis determined by the choice of the model; if the model is not correctly specified and not able to produce non-autocorrelated residuals, applying the bootstrap might be unsafe. Nonparametric methods are also robust to the presence of outliers.

[14]The bias of a bootstrap estimator is the difference between the mean of the bootstrap estimates and the sample estimate of the parameter based on 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 the bias of the bootstrap estimator.

Hall et al. (1995) show that overlapping blocks are more efficient in estimation than non-overlapping blocks. The moving-blocks scheme does not preserve important features of the original series such as stationarity, though. Politis and Romano (1994b) 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. However, whether block or stationary bootstrap is better in practice is a bit of an open question. Lahiri (1999) finds that the asymptotic mean squared error of the stationary bootstrap estimator always 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 (1994b) 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. One contribution of the Monte Carlo work reported at the end of this paper is providing additional evidence on the practical merits of these alternative methods. In particular, we show that the stationary bootstrap is appropriate for the specific statistical problem we address.

The stationary bootstrap resamples blocks of random length; the length of each block is sampled from an independent geometric distribution whose expected value equals the expected block size. Politis and Romano (1994b) suggest that the original series should be *wrapped* around a circle to fill blocks going past the last observation.[15] Our estimates and

[15] 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

inference are based on the version of stationary bootstrap that follows. Formally, in the simplest 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 estimated.[16] We use a nested bootstrap procedure to select the expected block length for the stationary bootstrap according to an automatic rule that solves a constrained optimization problem over a discrete set of values included in a closed interval whose length and boundaries increase with the sample size. The rule we propose minimizes the (root) mean squared error of the bootstrap estimator for the correlation coefficient over the subsample. 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 times for both the first and the second subsamples. At each complete resample of the original data, we estimate and collect $\widehat{\Delta\rho}^{*} = \left\{\widehat{corr\left(V_{A,t}^{2*}, V_{B,t}^{2*}\right)} - \widehat{corr\left(V_{A,t}^{1*}, V_{B,t}^{1*}\right)}\right\}$ to compose the bootstrap distribution of $\widehat{\Delta\rho}$.[17]

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.

[16] 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) $(Subsample\ size)\,\lambda \to \infty$. If these two conditions are respected, the choice of λ will not enter into first-order properties, such as bias or coverage error, of the bootstrap procedure. Getting the right rate for λ to tend to 0 will enter into second-order properties, instead.

[17] The standard independent bootstrap is a case of block bootstrap where the block length equals one. Specifically, it is a degenerate case of stationary bootstrap where $Prob\,(L = 1) = 1$. We use it when analyzing

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.[18] Any method for obtaining confidence intervals requires some conditions – rarely met in practice – to produce the intended confidence level.[19] It is known that t methods generally perform better than percentile.[20] Hall (1995) argues 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.[21] 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.[22] 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. A 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 of

non-autocorrelated time series as structural innovations, whose estimation we describe in a later section.

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

[19] We define coverage error as the difference between the nominal coverage probability and the true coverage probability. The order of accuracy of a confidence interval is the rate at which the errors of overcoverage or undercoverage of the $100 \times (1-\alpha)\%$ confidence interval limits approach zero.

[20] If the bootstrap distribution of a statistic is approximately normal and the bootstrap estimate of bias is small, an approximate α-level t interval for the parameter that corresponds to this statistic is $[statistic \pm t^* \times SE_{Boot}]$, where t^* is the critical value of the $t_{(n-1)}$ distribution with area α between $-t^*$ and t^* and n is the original sample size. The interval between the $\left[100 \times \frac{\alpha}{2}\right]$-th and the $\left[100 \times \left(1 - \frac{\alpha}{2}\right)\right]$-th percentile of the bootstrap distribution of a statistic is a α-level bootstrap percentile confidence interval for the corresponding parameter. 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 $\frac{1}{\sqrt{\min(Br, T-Br)}}$.

[21] One of the virtues of the percentile method – and of the related bias-corrected (BC) and bias-corrected and accelerated (BC_a) methods – is that intervals are equivariant under transformations of the parameters and cannot cover points beyond the possible range of statistic values. Appendix B describes the construction of bias-corrected and accelerated bootstrap confidence intervals and discusses the method.

[22] The coverage error is often substantial in empirical applications. In particulat, this is likely to occur when the bootstrap distribution is not symmetric.

α. An estimate for ϱ_α is obtainable through an additional round of bootstrapping. Namely, bootstrap iteration is intended to improve the accuracy of confidence intervals through nested levels of resampling to be used to estimate the coverage error and obtain a more precise coverage.[23] 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 generic 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.[24] The bootstrap estimate for ϱ_α is the solution, $\widehat{\varrho}_\alpha$, to the equation $\widehat{P}(\varrho_\alpha) = \alpha \therefore \widehat{\varrho}_\alpha = \widehat{P}^{-1}(\alpha)$.[25] The iterated bootstrap confidence interval

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

[24] We use $N^B_O = 1,000$ replications for the outer block bootstrap; $N^B_I = 500$ for the inner bootstrap. Note that, with bootstrap iteration, $N^B = N^B_O$. When iteration is not used, in the case of standard independent bootstrap, $N^B = 10,000$. Bootstrap samples are drawn using the same nonparametric method in the main and nested bootstraps. Also consider that there exists a serious trade-off between number of resamples (i.e., estimation accuracy) and computation time that must be taken into account.

[25] 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. Refer to the *Companion Technical Appendix* to this paper for further information on the algorithm.

for $\Delta\rho$ is then $I_1\left(\widehat{\varrho}_\alpha; V_{A,t}, V_{B,t}; V^*_{A,t}, V^*_{B,t}\right)$.

2.2 A Global Index for Comovement Changes

A measure of comovement changes based on the estimation of a global index for groups of countries, rather than just pairs, would help interpret results under a more general and comprehensive perspective. Assume we are interested in determining whether the pairwise correlations of the business cycle measures, $V_{m,t}$, for a group of M countries have jointly and significantly shifted after an exogenous break date, Br. Let $\widehat{\rho}^{1,V}_{m,n} = \widehat{corr}\left(V^1_{m,t}, V^1_{n,t}\right)$ and $\widehat{\rho}^{2,V}_{m,n} = \widehat{corr}\left(V^2_{m,t}, V^2_{n,t}\right)$ be the estimated correlation coefficients of variable V_t between countries m and n – with $m = 1, 2, ..., M$, $n = 1, 2, ..., M$, and $m \neq n$ – over subsamples 1 and 2, respectively. We define the empirical global index indicating the overall comovement variation among the countries in the sample as the weighted average sample correlation change

$$\widehat{WACC} = \sum_{m=1}^{M-1} \sum_{n=m+1}^{M} \omega_{m,n}\left(\widehat{\rho}^{2,V}_{m,n} - \widehat{\rho}^{1,V}_{m,n}\right),$$
$$\text{with } \omega_{m,n} = \frac{W_m + W_n}{\sum_{m=1}^{M-1}\sum_{n=m+1}^{M}(W_m + W_n)} > 0, \forall m, n,$$

where W_m and W_n are two elements of a $(M \times 1)$ vector, W, of positive variables used for constructing the weights, $\omega_{m,n}$. Note that $\sum_{m=1}^{M-1}\sum_{n=m+1}^{M}\omega_{m,n} = 1$ by construction. This index must be estimated over the common sample of the series of interest. The definition we adopt for it – a linear combination of correlation changes – justifies the application of iterated stationary bootstrap techniques to the data. To test the null of no joint comovement change for the groups of countries we consider, we derive bootstrap distributions for the $\widehat{WACC}$s and estimate confidence intervals for the corresponding population parameters using the steps described in the previous subsections.[26]

[26] For each group of countries, we consider the statistical test

$$\begin{cases} H_0 : WACC = 0 \\ H_1 : WACC \neq 0 \end{cases}.$$

For interval estimation, we use $N^B_O = 1,500$ outer bootstrap replications and $N^B_I = 750$ inner iterations. Note that, to make inference on the $WACC$s, the bootstrap framework already described for two countries should be extended to the case of M countries and $\frac{M(M-1)}{2}$ correlation changes.

2.3 Filtering Techniques for Output Gap Extraction

A key variable for understanding business cycles is output gap. The multivariate HP filter (HPMV) to be used for its extraction can be converted into a Kalman filter/smoother framework by assuming that macroeconomic series are composed of a trend, a cycle, and erratic elements not directly observable. The three components can be recovered by imposing sufficient restrictions on the trend and the cycle process. The procedure is less mechanical than the HP filter, as it allows calibration or maximum likelihood estimation of the parameters in the measurement and transition processes and provides a higher flexibility to deal with the unreliability of close-to-end estimates.[27] We apply Kalman algorithms to estimate output gaps after reformulating into a state-space model Laxton and Tetlow (1992)'s multivariate HP filter minimization problem[28]

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

where y_t is the logarithm of the level of real GDP, y_t^* is potential output, and $\xi_t \overset{i.i.d.}{\sim} N(0, S)$ is the residuals of a standard augmented Phillips curve, $\Delta \pi_t = \alpha \Delta \pi_{t-1} - \theta (y_t - y_t^*) + \delta q_{t-1} + \xi_t$, incorporating useful information for gap extraction.[29] The main measurement equation is

$$y_t = y_t^* + e_t$$

and the transition equations are

$$y_t^* = y_{t-1}^* + g_t^* + v_{1,t}$$

$$g_t^* = g_{t-1}^* + v_{2,t},$$

[27] When used as a two-sided filter (Kalman smoother), the methodology is affected again by the endpoint problem, though, as the HP filter.

[28] See Appendix C for a more detailed description of the reformulation.

[29] π_t is the quarterly inflation rate and q_t is a vector of temporary supply shocks. $\lambda_1 = 1,600$ and $\lambda_2 = 16$ with quarterly data.

with $e_t \overset{i.i.d.}{\sim} N(0, C)$, $v_t = \begin{pmatrix} v_{1,t} \\ v_{2,t} \end{pmatrix} = \begin{pmatrix} 0 \\ v_{2,t} \end{pmatrix} \overset{i.i.d.}{\sim} N(0, Q)$, $Q = \begin{bmatrix} 0 & 0 \\ 0 & Q_2 \end{bmatrix}$. We define $\sigma_0^2 = var\,(y_t - y_t^*)$, $\sigma_1^2 = var\left(\Delta y_{t+1}^* - \Delta y_t^*\right) = var\left(\Delta g_{t+1}^*\right)$, $\sigma_2^2 = var\,(\xi_t) = S$, $\lambda_1 = \frac{\sigma_0^2}{\sigma_1^2}$, and $\lambda_2 = \frac{\sigma_0^2}{\sigma_2^2}$.

For comparison purposes, we estimate output gaps through a macroeconomic production function depending on three standard variables: employed labor, employed capital, and total factor productivity.[30] We pick an aggregate Hicks-neutral Cobb-Douglas production function

$$Y_t = A_t F\left(K_{t-1}, L_t | \varphi\right) = A e^{\varepsilon_{y,t}} K_{t-1}^{1-\varphi} L_t^{\varphi},$$

with $0 < \varphi < 1$, implying constant returns to scale. We define capital input as the part of available capital stock actually used for production, labor input as the total number of hours worked, and total factor productivity as a measure for the level of efficiency of production. We use a version of the *perpetual inventory method* to estimate capital stock series.[31] Potential output is derived through estimates of the interrelations among the factors. The inputs plugged in the production function are determined exogenously, via univariate filters (labor and total factor productivity) and Johansen's cointegration method (capital).[32] Specifically, we make use of a method in which capital stock is necessary for the estimation of output gaps (Method 1) and of another one that rules out the complication of computing reliable series for capital (Method 2).

2.4 SVAR Models and Real Structural Innovations

The purpose of structural VAR ($SVAR$) estimation is to obtain a non-recursive orthogonalization of the error terms for impulse response analysis. An alternative to the recursive Cholesky orthogonalization requires the imposition of enough restrictions to identify the orthogonal (structural) components of the error terms. Faust and Leeper (1997) illustrate the reasons for which inference from structural VARs identified with long-run restrictions may

[30] We discuss the methodology in Appendix D.
[31] See Appendix E for details.
[32] Appendix F describes the statistical approach.

not be reliable. First of all, long-run effects of shocks would be imprecisely estimated in finite samples, this causing imprecise estimates of the other parameters in the model. Two additional reasons concern the identification problems inherent in models that aggregate across variables and/or over time. These latter problems are known and very general and apply to most empirical studies using time series. On the basis of simulations, St-Amant and Tessier (1998) argue that there are reasons to believe that Faust and Leeper's arguments are not devastating in practice. On the other hand, several recent papers explore this issue more fully in the context of DSGE models, finding that the method is not reliable. For completeness and comparability reasons with previous studies in the literature, we present results based on the analysis of real structural shocks estimated through long-run identifying restrictions on structural VARs and make inference on comovement changes across countries. Even if the structural interpretation is not convincing, the comovement tests are still potentially able to detect changes in certain factors driving the macroeconomy.

Let $Y_t = [g_t \; \pi_t \; \Delta r_t]^T$ be a $(k \times 1)$ vector of endogenous variables, where $g_t = \Delta y_t$ is the quarterly growth rate of real output, $\pi_t = \Delta p_t$ the quarterly inflation rate, and Δr_t the quarterly change of an annualized short-term real interest rate.[33] We estimate the $VAR\,(h)$,[34]

$$\Psi\,(L)\,Y_t = c_0 + e_t.$$

Structural assumptions are incorporated in the class of models $De_t = Bu_t$; e_t is the observed, reduced-form residuals in the VAR, u_t is the unobserved structural innovations, and D and B are $(k \times k)$ matrices. Under a set of conditions on e_t and u_t and the stationarity of the VAR, we have[35]

$$Y_t = \Theta\,(L)\,c_0 + \Theta\,(L)\,Bu_t = c_0' + Bu_t + B\sum_{i=1}^{\infty}\Theta_i u_{t-i},$$

[33] For the decomposition to be meaningful, log real output (y_t), log price index (p_t), and r_t should be $I\,(1)$. With quarterly data: $r_t = i_t - \pi_t^A$, where $\pi_t^A = \left[(1+\pi_t)^4 - 1\right]$; $\pi_t = p_t - p_{t-1}$ and i_t is an annualized short-term nominal interest rate (three-month money market interest rate in this paper).

[34] $\Psi\,(L)$ and, later, $\Theta\,(L) = [\Psi\,(L)]^{-1}$ are two lag polynomials. L is the lag operator.

[35] Let $\Sigma = E\,(e_t e_t')$ be the covariance matrix of the residuals, $D = I$, and $E\,(u_t u_t') = I$ (orthonormality).

with $\Theta(L) = [\Psi(L)]^{-1} = \left[I - \Psi_1 L - ... - \Psi_h L^h\right]^{-1} = I + \sum_{i=1}^{\infty} \Theta_i L^i$ and $\sum_{i=1}^{\infty} \Theta_i < \infty$.

$Z = [I - \Psi_1 - ... - \Psi_h]^{-1} B = \Theta(1) B$ is the (accumulated) long-run response of Y_t to structural innovations in the $(k \times 1)$ vector $u_t = \left[u_t^s \; u_t^{d_1} \; u_t^{d_2}\right]^T$. Y_t follows a stationary stochastic process responding to three types of orthogonal shocks. Since $k = 3$, we impose the following three long-run restrictions for the identification of the system:[36]

$$Z = \begin{bmatrix} z_{11} & 0 & 0 \\ z_{21} & z_{22} & z_{23} \\ z_{31} & z_{32} & 0 \end{bmatrix}.$$

Real structural shocks have standard economic interpretations as in much empirical literature: u_t^s is an aggregate supply shock; $u_t^{d_1}$ an aggregate demand shock of the first type, determined by fiscal policy; and $u_t^{d_2}$ an aggregate demand shock of the second type, generated by monetary policy.[37] The expected signs of the entries in Z are as follows: $z_{11} > 0$, $z_{21} < 0$, $z_{22} > 0$, $z_{23} > 0$, $z_{31} < 0$, $z_{32} > 0$. The three types of underlying structural shocks are thus identified and an estimate for u_t is $\widehat{u}_t = \widehat{B}^{-1}\widehat{e}_t$.[38]

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 (i.e., multi-sector international models with intermediate goods trade and one-sector models with either technology or monetary shocks), but such a result does not always hold.[39] For the peculiar case of a currency union two perspectives prevail: (i) the *European Commission View*, according to which

[36] As in Amisano and Giannini (1997), the number of additional restrictions for identification is $\frac{k(k-1)}{2}$.

[37] See, for example, Smets and Wouters (2007) in a DSGE setting.

[38] Each variable in the vector $\widehat{u}_t$ is expected to be white noise, since u_t is estimated as a linear combination of the observed residuals in the $VAR(h)$. This justifies the use of the (iterated) standard independent bootstrap for inference on correlation changes between structural shocks. Note that the estimation of structural innovations is conditional on the underlying economic model that suggests the restrictions to be imposed; hence, we can produce different structural components from the same model with different features or frictions.

[39] See Imbs (2004) for detailed references.

the removal of trade barriers should facilitate the diffusion of demand shocks, technology and knowledge spill-overs and lead to more synchronous output cycles; and (ii) the *Specialization Paradigm*, based on standard Heckscher-Ohlin trade theory, which 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.[40] However, if countries exhibit a trend towards intra- rather than inter-industry trade, the implied effects may be different. It turns out that, either if intra-industry trade is vertical or horizontal, then industry-specific shocks may make business cycles more synchronized.[41]

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 also by the intensity and nature of economic or productivity shocks and spill-over effects. In a situation of 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.[42]

In this section we try to give an answer to what is essentially an empirical question and

[40] These arguments can be extended to the more general case of regions characterized by trade connections.

[41] Trade is vertical when different countries specialize in different production stages of the same good and goods are differentiated by quality; it is horizontal when countries trade the same products with different attributes.

[42] Empirical research on international cycle synchronization has led to contrasting conclusions so far. 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 works are Bayoumi and Eichengreen (1992), Artis and Zhang (1997a) and (1997b), Rose and Engel (2000), and Bordo and Helbling (2003). Much more research in the field is in progress.

present results to assess the direction and the magnitude of the aforementioned effects and their implications in terms of cycle synchronization for the countries in the sample.

3.1 The Data

Our sample includes the twelve original EMU countries (EMU12) plus Denmark, Sweden, and the United Kingdom (EU15); the USA, Canada, Mexico, and Hong Kong.[43] Unless stated otherwise, series are quarterly and seasonally adjusted.[44] We keep the span of the econometric investigation between the end of the 1970s (EU) or the beginning of the 1980s (NAFTA) and the end of 2006 or the beginning of 2007. We start the samples later in those exercises including countries and variables for which longer series are unavailable. When comparing Hong Kong and US cycles, we go back to the mid-70s. With quarterly data, potential breakpoints are 1998.4 for the EU/EMU, 1993.4 for the NAFTA, and 1983.3 for Hong Kong/USA. With monthly data, they are 1998.12, 1993.12, and 1983.9.

What follows is a qualitative summary of the results. We describe cross-correlation changes and inference in tables at the end of this article. For further results not reported in the tables, refer to the website indicated on the front page. Table 1 sums up the degree of integration of the surveyed countries along two dimensions, participation in major trade agreements and enforcement of the exchange rate regime.

3.2 Joint Comovement Changes for Groups of Countries

We analyze eight non-mutually exclusive groups of countries and make inference on corresponding global indices of comovement.[45] Sample correlations from which $WACC$s are

[43] The set of EMU countries excludes Slovenia, Malta, and Cyprus. Denmark, Sweden, and the United Kingdom are currently outside the currency union, but were already part of the EU common market at the date of introduction of the Euro. The Danish currency is also pegged to the Euro. The currency area might have affected the synchronization of British and Swedish cycles with the rest of EMU countries: their currencies are still free to float, but, all other things being equal, specific relative prices (and real exchange rates) now move proportionally in the same direction with respect to all EMU countries, as nominal exchange rates vary.

[44] A more detailed description of the dataset is in Appendix A.

[45] EU countries: Austria, Belgium, Germany, Denmark, Spain, Finland, France, Greece, Italy, Netherlands, United Kingdom. EMU countries: Austria, Belgium, Germany, Spain, Finland, France, Greece, Italy, Netherlands. Core EU countries: Germany, Spain, France, Italy, United Kingdom. Core EMU countries: Germany, Spain, France, Italy. Non-Core EU countries: Austria, Belgium, Denmark, Finland, Greece, Netherlands. Non-Core EMU countries: Austria, Belgium, Finland, Greece, Netherlands. Deutsche Marc Bloc: Austria,

estimated can be computed only on the common samples. We weigh correlation changes by economic activity, as measured by annual GDP expressed in millions of current prices and current PPPs (US dollars), referred to 2006 as a base-year, and collected from the OECD database for all the countries.

Through the test of joint comovement change we propose, we are able to detect significant breaks in trade volume synchronization, which increased, at the European level and also find a number of nonnegligibly positive shifts in the correlations of real output measures and other variables for several subgroups of countries. Of particular interest is the case of the Deutsche Marc Bloc plus Finland; significance analysis tells us that joint comovement has risen for the countries in the area after 1999 with respect to most of the variables taken into account. Our investigation also outlines the existence of a core of European countries (at least Germany, France, and Spain), for which stock markets have become jointly more synchronized, and of a group of peripheral countries in the EU, whose stock markets have become more isolated with time. We are not able to detect significant global changes in comovement for NAFTA countries, with the only exception regarding final consumption expenditure; the higher synchronization for this variable suggests increased overall consumption risk-sharing among the US, Canada, and Mexico after 1994. Details and inference are presented in Tables 2a and 2b.

The evidence for breaks in this index is consistent with the deeper investigation described in the next sections and based on bilateral correlations.

3.3 Pairwise Comovement Changes – Real Economy

Output, Industrial Production, Consumption, and Investment

EU15/EMU12.[46] Tables 3 through 9 report select outcomes for European countries. Point estimates of pairwise correlation shifts are generally positive in the EU, as well as in

Belgium, Germany, Denmark, Finland, Netherlands. NAFTA countries: Canada, Mexico, USA.

While most intra-European bilateral exchange rates were rather volatile in the 1980s and 1990s, one group of countries – the Deutsche Marc Bloc – maintained narrow margins of exchange rate volatility. Finland was not part of the DM Bloc. In computing global indices, however, we include it for its geographical proximity to the countries in the Bloc within the borders of the EU.

[46] EU15 indicates the fifteen countries in the EU until May 2004. EMU12 indicates the twelve countries in the monetary union until January 2007.

the EMU. The crude numbers tell us that, regardless of the sign, statistically significant switches show up in proportions ranging between 16.7% and 30.6% of the total number of pairs considered in the EU. If we restrict attention to the currency union, these figures range between 11.1% and 36.2%. Most of the significant changes are positive for almost all business cycle measures. This pattern is clear with real output (Tables 3 and 4 for output gaps and Table 6 for growth rates), industrial production index (Table 7), and gross fixed capital formation (Table 9). As for real GDP, this point is even more apparent in Table 5, where we compare summary figures for inference on correlation changes between output gaps estimated using all the various methods described in the earlier sections. In the case of final consumption expenditure (Table 8), we notice a prevalence of positive point correlation shifts in the European Union, whereas small proportions of significant changes are similarly split between ups and downs. We detect, instead, a higher incidence of significantly negative switches in the case of the monetary union. These 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.[47] However, recent theoretical literature has challenged such conclusions.[48]

Overall, our results indicate parameter instability and a tendency to significant increases in cycle correlations among subgroups of European countries after the birth of the monetary union; a tendency that, not too surprisingly, does not concern only the countries that adopted

[47]The Backus-Kehoe-Kydland consumption correlation puzzle is the observation that consumption is less correlated across countries than output. In a situation of complete international markets, country-specific output risks should be pooled over countries and the time evolution of domestic consumption should not depend much on country-specific income shocks. As such, we should find that consumption is more correlated across countries than output.

[48]For example, some literature claims that international 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 (see Kaminsky et al., 2004 and Kaminsky, 2005).

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, industrial production index), 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 when real output measures and the growth rate of the industrial production index are taken into account, this revealing 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.[49] 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; although still not part of the Euro-area, Denmark is among the most open countries and, loosely speaking, its currency has been pegged to the Euro since 1999.

NAFTA. Table 10 presents a summary for the NAFTA countries. The agreement has enhanced comovement in North America, at least to some extent. Evidence is in favor of a more pronounced synchronization between Mexico and the USA in output and consumption expenditure. Significant positive shifts also regard Canada and Mexico as for consumption and fixed capital formation; output growth rates, instead, are significantly less correlated. Interestingly, 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 that started much earlier than 1994, the contextual Canadian specialization might have compensated tendencies to higher synchronization.[50]

[49] 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, and 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.

Also note that, in the complex case of Europe, there has been much heterogeneity in the well-known transformations that have been leading to deeper economic integration. Greece, for example, entered the currency union only in 2001, Slovenia in 2007, Cyprus and Malta in 2008.

[50] Similar inference is found when we look at the case of the CUSFTA, the trade agreement between Canada and the US enforced starting from January 1989.

HONG KONG. Table 13 describes comovement between the USA and Hong Kong. We detect significant decreases when looking at output gaps (Kalman filter) and final consumption expenditure. Evidence of lower correlations is weakly supported by falls in other point estimates (output gap estimated through the Kalman smoother and gross fixed capital formation). In most cases, correlations were positive and moderately high before the linked exchange rate system. On the other hand, a positive and non-significant correlation change for the GDP growth rate suggests that strong idiosyncrasies might have prevailed and prevented increasing synchronization between the two countries so far.

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.

EU15/EMU12. Evidence is mixed on the sign of point estimates, since they almost equally split between pluses and minuses. This contradicts the claim that the formation of a currency union should reliably and generally lead to more symmetric economic shocks.[51] Statistically significant shifts appear in proportions between 12.1% and 15.2% within the EU, but there is no clear pattern in the direction. Similar conclusions hold for EMU countries, for which the incidence of significant changes ranges between 11.1% and 16.7% of total observations. Despite a weak prevalence of positive switches in the correlation of first-type demand shocks, results do not point to a definite and unambiguous interpretation.

3.4 Pairwise Comovement Changes – Determinants of Comovement

In this part we analyze measures of trade and financial integration and their links with the business cycle. As economic integration gets stronger, the comovement features of interna-

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

tional trade volumes are expected to change.[52] As countries open up to trade, their economic linkages strengthen and this should affect cycle transmission. Consistent with a number of empirical studies is the view that countries with higher trade shares are likely to grow faster than other countries. Such a view is disputed, though, and does not necessarily imply that the direction of causation should go from trade to growth; much research has, in fact, emphasized the likelihood of a reverse causation. Whatever the sign of causation is, stylized facts attest the existence of generally high positive correlations between trade activity and real output within countries. However, the constitution of a free-trade area or a currency union – through the removal of barriers to the free exchange of goods, services, and factors of production; and the elimination of exchange rate volatility – may be accompanied by changes in the characteristics of the comovement between GDP and trade volumes.

Also, a number of articles have treated correlations in capital markets and other measures of international financial integration.[53] Nevertheless, evidence on linkages and interactions among international stock markets has been conflicting so far. Results and conclusions 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 the relatively recent economic and financial integration has 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 have become more correlated in Europe since 1999. About 95% of point estimates suggest correlation increases both in the EU as a whole and in 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 (Table 11). Significant rises involve most of European countries, including the largest economies.

[52] 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 confirmed by the generally high correlations between trade volumes over the entire sample.

[53] Financial integration may enhance risk sharing among countries, but also lead to specialization and negatively affect cycle synchronization. As mentioned ealier in this paper, arguments predicting opposite effects have also been proposed.

Correlations between total trade and real GDP have generally increased in Europe; exceptions regard Austria, Greece, and the UK. However, only in two cases are we able to notice significant shifts, positive in Denmark and negative in Greece.[54] These findings – witnessing more integration in real markets and a somewhat higher incidence of trade components on domestic products – are notable, since European countries were generally already open up to trade when, decades ago, the Economic Community, with a smaller number of member countries, was the main customs union in Europe.

NAFTA. Table 10 does not provide similarly strong evidence for the NAFTA region: 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 have been negligible for the three countries. However, total trade activities were already strongly correlated before the more recent episode of integration. Note that Mexico is the only country for which the correlation between trade volumes and GDP has significantly gone up since 1994; the Mexican economy has, in fact, switched to much higher levels of openness over the past fifteen years, which indicates an increasing dependence of its economy on trade.

HONG KONG. As from Table 13, the point estimate of the correlation between the trade activities of Hong Kong and the US has fallen since 1983, but we cannot reject the null of no change. Note that correlation was positive and large before that year. The correlation between trade and output has increased in Hong Kong, but – despite its international dynamism in recent decades – we do not succeed in detecting a statistically significant shift.

Stock Markets

EU15/EMU12. In Table 12 we examine comovement changes in monthly stock market

[54] Greece has historically been among the least dynamic countries in European markets, whereas Denmark boasts levels of openness among the highest.

returns for European countries.[55] Point estimates are negative in the majority of cases; but falls and rises show up in similar proportions, if we look only at statistically significant variations. We might conclude that correlations in European financial markets have not generally increased since the creation of the currency area or that evidence is still inconclusive. However, a few significant rises and the results on global indices already reported in Tables 2a and 2b provide clear support for the contrasting claim that at least the largest markets in terms of domestic capitalization are more synchronous today than years ago. 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 have become significantly more isolated. It follows that the emergence of a core of countries and the formation of a peripheral group in European financial markets is probably a more plausible description of the current situation.

NAFTA/HONG KONG. Table 13 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. We find a small non-significant fall in the correlation of stock market returns between Hong Kong and the USA; also in this case, comovement was high before 1983.

We find positive point correlation changes between stock markets and real GDPs for all the countries in the sample and significant rises in Germany, Denmark, the UK, and Mexico.

4 Reliability of the Testing Strategy

Earlier, we discussed the main features of block bootstrap methods and their theoretical differences. It should be clear at this point why, 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 our dataset. In this section, we explore the properties of the method we propose for inference and compare

[55] Returns are calculated as $R_t = \log\left(\frac{Ind_t}{Ind_{t-1}}\right)$, where Ind_t is the stock market index.

it to the techniques described in a closely related article, Doyle and Faust (2005), and to alternative bootstrap solutions. We justify our econometric choice by looking at the outcomes of extensive Monte Carlo experiments that show the goodness of our testing strategy when compared to other competing statistical devices of the same class.

4.1 Comparison with Doyle and Faust (2005)

We start with a naïve assessment of the statistical properties of the formulated test. We apply our econometric methods to the same dataset used in the related 2005 article by Doyle and Faust. We consider time series on real GDP, consumption, and investment for the G7 countries; data are quarterly and range from the first quarter of 1960 to the last quarter of 2002. We focus on the growth rates of real output and on the cyclical components of real output, consumption, and investment estimated through a standard HP filter.

At a first stage of analysis we restrict the original samples to match those in this paper, impose the exogenous breakpoints used in the two cases of the NAFTA area and Europe (1993.4 and 1998.4), and statistically test for changes in the correlation coefficients between corresponding business cycle measures for all the pairs of countries that fall in the two macro areas. Specifically, we investigate seven pairs of countries and four cycle measures. Point estimates of correlation changes are negative between Canada and the USA, but in the case of investment. In Europe, point correlation shifts are generally positive with just a few exceptions. We are able to detect seven (out of twenty-eight) significant changes; all of them pertain Europe (a total of twenty-four combinations), two are negative and regard consumption. These results validate and give further support to what we find in our main analysis using different data sources: a general increase in the degree of comovement among European countries as witnessed by a majority of positive point estimates of correlation shifts, further corroborated by a nonnegligible proportion of significantly positive variations.

The attempt to directly relate the inference properties of our testing strategy to those resulting from comparable tests in Doyle and Faust (2005) produces additional interesting outcomes. This time we pick the same extended samples as in their article and impose the same breakpoints they estimate for each variable through maximum likelihood. We consider the case in which they allow for the presence of one break and investigate unconditional correlations in the data. Our econometrics manages to detect eleven significant correlation changes (out of twenty-eight combinations), Doyle and Faust's is able to detect ten. This finding suggests – at least to a first approximation – that our test based on nonparametric bootstrap techniques is likely to perform at least as well as the testing device constructed by Doyle and Faust, based, instead, on a parametric version of the bootstrap. However, a stronger stand on this point may be taken only after running proper Monte Carlo simulations.

4.2 Monte Carlo Evidence

To assess 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 clear 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 eventually opt for the scheme that generates negligible bootstrap biases, produces intervals with actual coverage probabilities close to nominal levels, and induces high statistical power in corresponding tests.[56]

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 14a and 14b), we choose the following representation for each pair of variables:

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

[56] A $\pm 5\%$ tolerance band for the actual coverage probability around the nominal level is acceptable in empirical works.

where $\left\{F_i^{1,2}\right\}_{i=1}^{h}$ and $\Omega^{1,2}$ are (2×2) matrices. Superscripts indicate the subsample over which the model is estimated.[57] 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.[58] 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 in Appendix G. Of course, the ideal would be to attain estimated coverage probabilities that are close to the nominal level, α, and high estimated powers. We compare simulated sizes and powers to these ideals.

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.[59] 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 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

[57] 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.

[58] 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.

[59] 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.

data, we estimate a unique VAR on the whole 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 main subsamples remain unchanged. $\widehat{c}_{A,B}$ and $\{\widehat{F}_i\}_{i=1}^{h}$ do not vary from the first sample to the second. We use the steps described in the appendix to estimate the coverage probabilities of confidence intervals under the null of no correlation variation after the break (Table 14c). Given the new set of assumptions in the DGP, the *true* $\Delta\rho$ is zero by construction.

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.[60] 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 14a-c report the results from Monte Carlo experiments and support the view that our method has somewhat better size properties than the others while retaining reasonable power. On such bases, we conclude that our ability to identify significant correlation switches is nonnegligible and that our testing strategy is accurate also when samples are small.

[60] Namely, we compare the performance of the following bootstrap schemes: iterated stationary, iterated standard independent, stationary, standard independent, non-overlapping block, iterated overlapping block, overlapping block, and iterated parametric (under the assumption of correct specification of the model).

5 Conclusions

In this paper we describe tools to 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. Extensive Monte Carlo simulations effectively 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 three groups of countries and three important instances of international economic integration (European EMU, NAFTA, US/Hong Kong linked exchange rate system) and take them as exogenous breaks. We find moderate signs of higher levels of cycle synchronization in Europe after the introduction of the Euro, despite the large correlations already prevailing in the area during the pre-EMU period. Inference on a suitable global index for groups of countries show widespread higher degrees of comovement, particularly in specific areas, among which the cases of DM Bloc plus Finland and core EU deserve a mention. Also, 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) and provide empirical evidence in favor of the claim that the formation of the Euro-area has been followed by stronger economic integration in real markets and by generally more evident comovement concerning real economic variables. Financial integration, measured by the synchronization of stock markets, exhibits a peculiar pattern: correlations have become stronger among core EU/EMU countries, whereas a peripheral group of non-core countries (particularly Austria and Belgium) has become more isolated over time.

Generally negligible global correlation variations are found in the NAFTA area following 1994, with the only exception regarding final consumption expenditures series, which are more synchronous. This finding suggests increased consumption risk-sharing among the three countries in the trade agreement. On the other hand, we notice increased pairwise comovement only between Mexico and the US and, to some extent, between Mexico and Canada, the latter case only with respect to a few variables other than output (consumption, gross fixed capital formation, and stock market returns). Output growth rates are significantly less synchronized between Canada and Mexico. The minimal size of the impact of the NAFTA for the US economy could be expected, though, since the United States had very low tariffs even before the trade agreement. Signs of a more pronounced synchronization between Hong Kong and the US after 1983 are absent; instead, we estimate a few significant declines in the correlations of output and consumption expenditure.

For a correct interpretation of the results, one should consider the fact that the majority of estimated point correlation changes is positive and that, in many cases, our testing device may simply fail to reject a false null of no comovement change. It is remarkable, however, that we succeed in detecting a nonnegligible set of significantly more correlated variables despite the small samples. With some caveats, we give empirical support to the endogeneity theories predicting more synchronous cycles as economic linkages get tighter, although international integration is still an ongoing process and an answer to the question of whether the higher cross-country synchronization we find is just transitory or permanent can only be left to future studies. As in some recent literature in the field, our results do not simply suggest that globalization and integration have induced generally 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.

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7 Technical Appendix

We sketch some of the estimation and testing techniques. For further discussion and details, refer to the *Companion Technical Appendix*.

Appendix A. Description of the Data[61]

Data for EU countries and the USA are generally from EUROSTAT; US final consumption expenditure is from the OECD. Series for Canada are from the Canadian National Statistical Agency; real effective exchange rates are from EUROSTAT; final consumption expenditure are from the OECD. Mexican data are collected from the Instituto Nacional de Estadística Geografía e Informática, except for real effective exchange rates and final consumption expenditure (OECD). Hong Kong series are taken from the Census and Statistics Department of the Government of Hong Kong; the stock market index is provided by the Research Department of the Hong Kong Monetary Authority. All series on the industrial production index are from the OECD, as well as on gross fixed capital formation for Mexico and Canada.[62]

[61] A full description is available in the *Companion Technical Appendix*, Section *"Description of the Data"*.

[62] The industrial sector – from which data for the construction of the industrial production index are taken – includes manufacturing, mining, and utilities. Although these sectors contribute only to a small portion of GDP, they are highly sensitive to interest rates and consumer demand.

Final consumption expenditure and gross fixed capital formation might be more sensitive to international linkages than other variables. International integration might lead to consumption insurance, for example.

Appendix B. BC_a Bootstrap Confidence Intervals

BC_a intervals modify the percentile method by adjusting percentiles to correct for bias and skewness at the same time through the estimation of a bias-correction term and an acceleration term, are accurate in a wide variety of cases, have reasonable computation requirements, do not produce excessively wide intervals, but might lead to inaccurate results with autocorrelated series.[63] BC_a confidence intervals are second-order accurate, under some regularity conditions and when applied to a suitable framework. This means that the overcoverage or undercoverage of the $100 \times (1-\alpha)\%$ confidence interval approaches zero at a rate related to $\frac{1}{\min(Br, T-Br)}$.[64]

Assume that $\widehat{\Delta\rho}^{*}_{n^B}$ is the n^B-th bootstrap replication of $\widehat{\Delta\rho}$. Let $\widehat{G}(c)$ be the empirical distribution function of N^B bootstrap replications $\widehat{\Delta\rho}^{*}$:

$$\widehat{G}(c) = \frac{\sum_{n^B=1}^{N^B} 1\left\{\widehat{\Delta\rho}^{*}_{n^B} < c\right\}}{N^B}.$$

A two-sided α-level BC_a interval for $\Delta\rho$, $\left[\widehat{\Delta\rho}^{\left(\frac{\alpha}{2}\right)}_{BC_a}; \widehat{\Delta\rho}^{\left(1-\frac{\alpha}{2}\right)}_{BC_a}\right]$, with $\alpha \in (0,1)$, is defined in terms of $\widehat{G}$ and two numerical parameters to be estimated: a bias-correction term, bc, and an acceleration term, acc, which accounts for the possible rate of change of the standard error of the estimator with respect to the true parameter. The endpoints in the interval are

$$\begin{aligned}
\widehat{\Delta\rho}^{\left(\frac{\alpha}{2}\right)}_{BC_a} &= \widehat{G}^{-1}\left[\Phi\left(\widehat{bc} + \frac{\widehat{bc} + z^{\left(\frac{\alpha}{2}\right)}}{1 - \widehat{acc}\left(\widehat{bc} + z^{\left(\frac{\alpha}{2}\right)}\right)}\right)\right], \\
\widehat{\Delta\rho}^{\left(1-\frac{\alpha}{2}\right)}_{BC_a} &= \widehat{G}^{-1}\left[\Phi\left(\widehat{bc} + \frac{\widehat{bc} + z^{\left(1-\frac{\alpha}{2}\right)}}{1 - \widehat{acc}\left(\widehat{bc} + z^{\left(1-\frac{\alpha}{2}\right)}\right)}\right)\right],
\end{aligned}$$

where Φ is the standard normal cumulative distribution function; $z^{\left(\frac{\alpha}{2}\right)}$ and $z^{\left(1-\frac{\alpha}{2}\right)}$ are, respectively, the $\left[100 \times \frac{\alpha}{2}\right]$-th and the $\left[100 \times \left(1-\frac{\alpha}{2}\right)\right]$-th percentile of a standard normal dis-

[63] When skewness is large or data are autocorrelated, the acceleration term should be set to zero and BC_a intervals would collapse into BC intervals. If the bootstrap distribution is symmetric around the sample estimate, the bias-correction term is null and BC and percentile intervals will agree.

[64] Efron and Tibshirani (1993).

tribution. In its simplest form, the BC_a algorithm estimates the bias-correction term as

$$\widehat{bc} = \Phi^{-1}\left\{\widehat{G}\left(\widehat{\Delta\rho}\right)\right\} = \Phi^{-1}\left\{\frac{\sum_{n^B=1}^{N^B} 1\left(\widehat{\Delta\rho}^{*}_{n^B} < \widehat{\Delta\rho}\right)}{N^B}\right\},$$

i.e., as Φ^{-1} of the proportion of the bootstrap correlation changes that are less than $\widehat{\Delta\rho}$. The acceleration term, *acc*, measures how quickly the standard error changes on the normalized scale. Estimating *acc* is more difficult. Its estimation depends on the form of the bias and on how we choose to represent it. The focus is on the skewness of the distribution of the estimator in a neighborhood of $\Delta\rho$. DiCiccio and Efron (1996) show that *acc* should be estimated in terms of the skewness of the score function in a neighborhood of $\Delta\rho$:

$$\widehat{acc} = SKEW_{\widehat{\Delta\rho}=\Delta\rho}\left\{\frac{1}{6}\frac{\partial}{\partial\left(\Delta\rho\right)}\log\left[\frac{\partial}{\partial\left(\widehat{\Delta\rho}\right)}G_{\Delta\rho}\left(\widehat{\Delta\rho}\right)\right]\right\}.$$

A nonparametric numerical method based on the jackknife – used to estimate the second and the third moments of $\widehat{\Delta\rho}$ – yields the following expression for $\widehat{acc}$:

$$\widehat{acc} = \frac{1}{6}\frac{\sum_{i=1}^{T}\left(\widehat{\Delta\rho}-\widehat{\Delta\rho}_{-i}\right)^3}{\left[\sum_{i=1}^{T}\left(\widehat{\Delta\rho}-\widehat{\Delta\rho}_{-i}\right)^2\right]^{\frac{3}{2}}},$$

where $\widehat{\Delta\rho}_{-i}$ is the sample change of correlation over the two contiguous subsamples obtained by computing the value of the statistic $\widehat{\Delta\rho}$ after removing the i-th observation from the concatenated vectors $\left[\begin{array}{c}\left\{V^1_{A,s}\right\}_{s=1}^{Br} \\ ------------ \\ \left\{V^2_{A,s}\right\}_{s=Br+1}^{T}\end{array}\right]$ and $\left[\begin{array}{c}\left\{V^1_{B,s}\right\}_{s=1}^{Br} \\ ------------ \\ \left\{V^2_{B,s}\right\}_{s=Br+1}^{T}\end{array}\right]$.

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

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

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

where y_t is the logarithm of the level of real GDP and y_t^* is potential output.[65] The ordinary HP filter is augmented with the residuals, ξ_t, of an economic relationship that incorporates useful information for output gap extraction

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

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):

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

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

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

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

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

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

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 $(C.5)$ is an

[65] Laxton and Tetlow (1992).

identity; $(C.6)$ incorporates the hypothesis of persistence of the NAIRU.[66] $(C.5)$ and $(C.6)$ are representable in reduced form

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

The simple economic relationship we use is a standard augmented Phillips curve[67]

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

where $\pi_t = p_t - p_{t-1}$ is the inflation rate, q_t is a vector of temporary supply shocks.[68]

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

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

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 $(C.7)$, with $\begin{pmatrix} v_{2,t} \\ v_{2,t} \end{pmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{pmatrix} 0 \\ v_{2,t} \end{pmatrix} = v_t' \overset{i.i.d.}{\sim} N\left(0, \begin{bmatrix} Q_2 & Q_2 \\ Q_2 & Q_2 \end{bmatrix}\right)$.

[66] This assumption is particularly sensible in the case of continental Europe.

[67] We calibrate θ, α, and δ by running OLS on $\Delta\pi_t = \alpha\Delta\pi_{t-1} - \theta\left(y_t - y^*\right) + \delta q_{t-1} + \xi_t = \theta y^* + \alpha\Delta\pi_{t-1} - \theta y_t + \delta q_{t-1} + \xi_t$ where the simplifying assumption of constant NAIRU holds.

[68] 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.

We apply filter and smoother to the model[69]

$$Y_t = HX_t + GZ_t + u'_t \tag{C.10}$$

$$X_{t+1} = AX_t + v'_{t+1} \tag{C.11}$$

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

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

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

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

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

Appendix D. Macroeconomic Filters

We choose the aggregate Hicks-neutral Cobb-Douglas production function $Y_t = Ae^{\varepsilon_{y,t}} K_{t-1}^{1-\varphi} L_t^{\varphi}$, with constant returns to scale. Exogenous time-varying technology ($TFP_t = A_t = Ae^{\varepsilon_{y,t}}$) does not exhibit deterministic trends, $\varepsilon_{y,t}$ is a random error capturing what is not included

[69] If equation ($C.4$) 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, ($C.10$) and ($C.11$), with the imposed structure.

θ and S can be estimated by OLS on ($C.8$). 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.

in the constant part of technical progress. Official data on capital stocks are rare and national sources are not always reliable and easily comparable; we use a version of the *perpetual inventory method* (PIM) to compute country-specific time series for this variable. We name those capital stock series potential capital, K_t^*, i.e., the maximum level of physical capital that is usable in the production process. Potential capital stock may be significantly related to real output fluctuations, at least in the long run; as in Shaikh and Moudud (2004), we use a statistical methodology based on the derivation of a cointegration relationship between real GDP and potential capital stock. We thus estimate employed capital stock series, K_t, i.e., the part of total capital actually employed for production. We use data on labor force (LF_t), unemployment rates (un_t), and average actual weekly hours worked by each worker ($AWHW_t$) to obtain quarterly series for employed labor input through

$$L_t = (1 - un_t) \times (LF_t \times AWHW_t \times 13) = (1 - un_t) \times L_t^S,$$

under the assumptions that a year comprises 52 weeks and a quarter 13 weeks.[70] We estimate NAIRU rates, un_t^N, for each country using the Phillips curve[71]

$$\left(un_t - un_t^N\right) = \psi\left(\pi_t - \pi_{t-1}\right) = \psi\Delta^2 p_t \therefore \Delta un_t - \Delta un_t^N = \psi\Delta^3 p_t,$$

with $\psi < 0$. NAIRU is assumed to be persistent and to change gradually; we impose $\Delta un_t^N \approx 0$ on the Phillips curve:

$$\Delta un_t = \psi\Delta^3 p_t \therefore un_t^N = un_t - \frac{\Delta un_t}{\Delta^3 p_t}\Delta^2 p_t.$$

Total factor productivity is residually derived from the log version of the production

[70] L_t^S is total labor supply.

[71] This may produce outliers for un_t^N, which we replace with the average of the two adjacent observations.

function as $\widehat{tfp}_t = \widehat{a}_t = y_t - (1-\widehat{\varphi})\,k_{t-1} - \widehat{\varphi} l_t$, with $\widehat{\varphi} = 0.6$.[72] Potential output is

$$y_t^* = tfp_t^* + (1-\widehat{\varphi})\,k_{t-1}^* + \widehat{\varphi} l_t^*,$$

with $tfp_t^* = HP\left(\widehat{tfp}_t\right)$, $l_t^* = \log(L_t^*)$, and $L_t^* = \left[1 - HP\left(un_t^N\right)\right] HP\left(L_t^S\right)$. $HP(\cdot)$ is the *Hodrick-Prescott operator*, implying the application of a univariate HP filter on its argument.

An alternative procedure avoids the complication of estimating capital stock. We can derive the time-varying marginal productivity of labor as $\mu_t = \frac{\partial Y_t}{\partial L_t} = \varphi \frac{Y_t}{L_t}$ and then apply logs to both the sides of the latter to get $y_t = l_t + \log(\mu_t) - \log(\varphi)$. Potential output is

$$y_t^* = l_t^* + \log(\mu_t^*) - \log(\widehat{\varphi}),$$

with $\mu_t^* = HP(\widehat{\mu}_t)$ and $\widehat{\mu}_t = \widehat{\varphi}\frac{Y_t}{L_t}$.

Appendix E. Perpetual Inventory Method

Let K_t^* be the level of real potential capital stock at period t – i.e., the maximum level of physical capital that can be used in the production process – and I_t the level of real investment at time t. In the capital accumulation equation

$$K_{t+1}^* = (1-d)\,K_t^* + I_t,$$

where d is the depreciation rate, assumed to be constant over time and across countries, we divide left and right-hand sides by Y_t:[73]

$$\frac{K_{t+1}^*}{Y_t} = (1-d)\,\frac{K_t^*}{Y_t} + \frac{I_t}{Y_t} \therefore (1+g)\,\kappa_{t+1} = (1-d)\,\kappa_t + \iota_t,$$

[72] Labor share of output, φ, is difficult to estimate correctly through an aggregate production function and with time series data. We use a standard calibration in the growth literature.

[73] Official estimates of capital stocks for different countries are in general based on different assumptions about depreciation rates. This is appropriate as country-specific factors influence service lives. However, only a few countries have investigated service lives with particular care, among them the United States. Therefore, it seems preferable to assume identical depreciation rates across countries for the purpose of international comparisons. Such a standardized approach is also adopted by Maddison (1995) and O'Mahony (1996).

with g being the steady-state growth rate of real output, $\kappa_t = \frac{K_t^*}{Y_t}$, and $\iota_t = \frac{I_t}{Y_t}$. At the steady state $\kappa_{t+1} = \kappa_t = \overline{\kappa}$ and $\iota_t = \overline{\iota}$. Then

$$(1+g)\,\overline{\kappa} = (1-d)\,\overline{\kappa} + \overline{\iota} \therefore \overline{\kappa} = \frac{\overline{\iota}}{d+g}.$$

We assume the economy is at its steady-state potential capital-output ratio ($\overline{\kappa}$) at the time from which we have available investment data. Knowing $\overline{\iota}$, d, and g we can compute $K_0^* = \overline{\kappa} Y_0$. To derive $\overline{\kappa}$, we set $d = 0.07$ (annual rate; a good approximation for most developed countries) and then construct g – the steady-state annual growth rate of output – as a weighted average of the country-specific average growth rate, g_a^C, during the first ten years for which we have output and investment data[74] and the average world growth rate, g_a^W (equal to 4.23% per year).[75] Based on Easterly et al. (1993), we give a weight of 0.75 to the world growth rate and a weight of 0.25 to the country-specific growth rate.[76] We compute $\overline{\iota}$ as the average investment rate during the first ten years for which there are data. To reduce the influence of business cycles in deriving Y_0, we use the average real output value over the first three years of the sample. Given depreciation, our *guess* on the initial potential capital stock value becomes relatively unimportant years later.

Appendix F. Estimation of Employed Capital Stock Series

Following Shaikh and Moudud (2004), we statistically derive employed capital under the implicit assumption that there exists a long-run relationship between real output and potential capital stock. We estimate a cointegrating vector between the log of real GDP and the log of potential capital (potential is normalized so that employed capital fluctuates around it). The method relies on Johansen's cointegration analysis and starts from the identity $Y_t = \frac{Y_t^C}{K_t^*} \frac{Y_t}{Y_t^C} K_t^*$, where Y_t^C is economic capacity, here defined as the desired level of output obtainable from given plant and equipment. Let $r_{1,t} = \frac{K_t^*}{Y_t^C}$ = potential capital/capacity ratio

[74] With quarterly data country-specific average annual growth rate of output is $g_a^C = \sqrt[9]{\frac{\sum_{s=37}^{40} Y_{t+s}}{\sum_{s=1}^{4} Y_{t+s}}} - 1$.

[75] See Easterly and Levine (2001).

[76] That is, $g = 0.75 g_a^W + 0.25 g_a^C$.

and $r_{2,t} = \frac{Y_t}{Y_t^C}$ = capacity utilization rate. We then rewrite the identity in its log form

$$y_t = -\log(r_{1,t}) + \log(r_{2,t}) + k_t^* = -\log(r_{1,t}) + \varepsilon_t^{r_2} + k_t^*, \qquad (F.1)$$

and assume that actual output fluctuates around capacity over the long run, so that the rate of capacity utilization, $r_{2,t}$, oscillates around 1. The implication is that firms maintain some correspondence over time between physical capacity and utilization levels. Under this hypothesis, $\varepsilon_t^{r_2} = \log(r_{2,t})$ is a random error term whose expected value is zero.

Let g_t^v be the growth rate of potential capital/capacity ratio and g_t^k the growth rate of potential capital. We make the behavioral assumption that the growth rate of potential capital/capacity ratio changes over time, partly in response to an autonomous technical change and partly in response to embodied technical changes that depend on the rate of potential capital accumulation, $g_t^v = b_1 + b_2 g_t^k$. By integrating both sides, we get

$$\log\left(\frac{K_t^*}{Y_t^C}\right) = b_0 + b_1 t + b_2 \log(K_t^*) + \varepsilon_t^{r_1} \therefore \log(r_{1,t}) = b_0 + b_1 t + b_2 k_t^* + \varepsilon_t^{r_1}, \qquad (F.2)$$

with $\varepsilon_t^{r_1}$ being an additional random error term with zero expectation and autocorrelation and finite variance. By substituting $(F.2)$ in $(F.1)$, we obtain

$$k_t^* = \frac{b_0}{1-b_2} + \frac{b_1}{1-b_2}t + \frac{1}{1-b_2}y_t + \frac{1}{1-b_2}\left(\varepsilon_t^{r_1} - \varepsilon_t^{r_2}\right) = a_0 + a_1 t + a_2 y_t + \varepsilon_t^k, \qquad (F.3)$$

which states that y_t and k_t^* are cointegrated, possibly up to a linear deterministic trend in the cointegrating vector. Johansen's approach is used to estimate such a vector (i.e., the coefficients of the long-run relationship that ties y_t and k_t^*), which, in turn, yields a long-run estimate for the level of employed capital, $k_t = \widehat{a}_0 + \widehat{a}_1 t + \widehat{a}_2 y_t$.[77]

[77] Cointegration requires some choice of scale, which is usually accomplished by arbitrarily setting the cointegration coefficient of the first variable in the cointegrating vector equal to one. There is a common *belief*, originating from estimates based on surveys, that when utilization rises above a given threshold, price inflation will increase. In fact, when firms attempt to produce beyond their *normal* levels, the cost of producing the additional output becomes increasingly expensive if the firm's production process exhibits diminishing returns to scale. The higher cost then translates into higher prices. The normalization to one reflects this property in a different way: given capital share of output, $(1-\varphi)$, actual capital above potential capital translates into a tendency for actual output to rise above its potential, thus inducing price inflation.

Appendix G. Monte Carlo Experiments

The following are the six steps to perform the Monte Carlo experiments. Notation is referred to the model

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

here assumed to be the true data-generating process. Superscripts indicate the subsample over which the model is estimated. The two estimated innovation covariance matrices are assumed to be constant over their respective subsamples.

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 $(T - Br)$.[78] 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.

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

Step 5. We calculate the proportion of α-level confidence intervals covering the *true* $\Delta\rho$ (estimated coverage probability).[79] 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 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.[80] 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.

To simulate the presence of the Great Moderation in the DGP and roughly match the select data, we estimate a unique VAR on the whole 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. $\widehat{c}_{A,B}$ and $\left\{\widehat{F}_i\right\}_{i=1}^{h}$ do not vary. We use the steps above to estimate the coverage probabilities

[79] 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.

[80] 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 $\widehat{\pi(H_1)} = \frac{\sum_{i=1}^{N^M} 1\{0 \notin I_i(\alpha;\Delta\rho)\}}{N^M}$.

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.

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
COUNTRY WITH A LINKED EXCHANGE RATE SYSTEM WITH US DOLLAR (10.17.1983)	
Hong Kong (HK)	

[(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

Global Index - Weighted Average Correlation Changes

Cycle Measure - Filtering Method	EU		EMU		Core EU		Core EMU	
Real GDP - HPMV (KF) (1991.4-2006.2)	0.187	u	0.141	u	0.347	u[1]	0.362	u[1]
Real GDP - HPMV (KS) (1991.4-2006.2)	0.243	u	0.105	u	0.341	u[1]	0.137	u[1]
Real GDP - Production Function (1) (1991.4-2006.2)	**0.524**[a]	U	0.321[a]	u	**0.598**	**U**	**0.413**	U
Real GDP - Production Function (2) (1991.4-2006.2)	**0.455**[a]	U	0.246[a]	u	**0.534**	U	0.242	u
Real GDP - Growth (1991.2-2006.2)	0.062	u	0.089	u	0.198	u[2]	0.106	u[2]
Industrial Production Index - Growth (1) (1980.1-2007.1)	0.150[c]	u	0.103[d]	u	0.209	u	0.106	u
Industrial Production Index - Growth (2) (1991.2-2007.1)	0.011	u	0.054[c]	u	0.098	u	-0.044	d
Final Consumption Expenditure - HP (1991.1-2006.2)	0.137	u	0.016	u	0.356	u[3]	0.151	u[3]
Gross Fixed Capital Formation - HP (1991.1-2006.2)	0.136	u	0.076	u	0.118	u	-0.055	d
Trade Activity (Imports+Exports) - HP (1991.1-2006.2)	**0.315**	(U)	0.232	u	0.258	u[4]	0.066	u[4]
Stock Market Index - Return[h] (1990.2-2006.11)	-0.032[e]	d	-0.058[e]	d	0.084[f]	u[5]	**0.102[f]**	U

EU: AT, BE, DE, DK, ES, FI, FR, GR, IT, NE, UK. **EMU**: AT, BE, DE, ES, FI, FR, GR, IT, NE. **Core EU**: DE, ES, FR, IT, UK. **Core EMU**: DE, ES, FR, IT. **Non-Core EU**: AT, BE, DK, FI, GR, NE. **Non-Core EMU**: AT, BE, FI, GR, NE. **DM Bloc + Finland**: AT, BE, DE, DK, FI, NE. **NAFTA**: CA, MEX, USA. **Note**: Finland was not formally part of the Deutsche Marc (DM) Bloc. In computing global indices, however, we include it for its geographical proximity to the countries in the Bloc within the borders of the EU.

Breakpoint Date (Europe, Quarterly Data): 1998.4. **Breakpoint Date (Europe, Monthly Data)**: 1998.12. **Breakpoint Date (NAFTA, Quarterly Data)**: 1993.4. **Breakpoint Date (NAFTA, Monthly Data)**: 1993.12.

Bootstrap Replications: 1500. **Bootstrap Iterations**: 750.

[a]Does not include: AT, FI, GR. [b]Does not include: AT. [c]Also includes: IE, LUX, PT, SE. [d]Also includes: IE, LUX, PT.

[e]Does not include: IT. Includes: IE. [f]Does not include: IT. [g] Also includes: IE. [h]Monthly data.

[1]1991.4-2006.3. [2]1991.2-2006.3. [3]1991.1-2007.1. (4)1991.1-2006.3. [5]1987.8-2006.11. [6]1980.4-2006.3. [7] 1980.2-2006.3. [8]1980.2-2007.1. [9]1991.2-2007.1. [10]1980.1-2006.4. [11]1991.1-2006.2. [12]1981.1-2006.3. [13]1983.2-2006.11.

Symbols and Notation. u: non-significantly positive correlation change; U: positive correlation change (significant at 10% level); **U**: positive correlation change (significant at 5% level); d: non-significantly negative correlation change; D: negative correlation change (significant at 10% level); **D**: negative correlation change (significant at 5% level). **Entries in parentheses**: bias-correction is applied. **Correlation Changes in bold**: significant at either 5% or 10% level.

Table 2a. Weighted Average Correlation Changes (WACCs) (1)

Global Index - Weighted Average Correlation Changes

Cycle Measure - Filtering Method	Non-Core EU		Non-Core EMU		DM Bloc + Finland		NAFTA	
Real GDP - HPMV (KF) (1988.4-2006.2)	0.260	u	0.083	u	**0.465**	U[1]	0.181	u[6]
Real GDP - HPMV (KS) (1988.4-2006.2)	0.230	u	0.088	u	**0.341**	U[1]	0.262	u[6]
Real GDP - Production Function (1) (1991.4-2006.2)	---	-	---	-	**0.645**[b]	**U**	---	-
Real GDP - Production Function (2) (1991.4-2006.2)	---	-	---	-	**0.572**[b]	**U**	---	-
Real GDP - Growth (1988.2-2006.2)	0.035	u	-0.025	d	0.101	u[2]	-0.060	d[7]
Industrial Production Index - Growth (1) (1980.1-2007.1)	0.116[c]	u	0.077[d]	u	0.145	u	0.025	u[8]
Industrial Production Index - Growth (2) (1988.2-2007.1)	0.086[c]	u	0.073[c]	u	0.042	u[9]	---	-
Final Consumption Expenditure - HP (1988.1-2006.2)	-0.127	d	-0.207	d	0.125	u[3]	**0.522**	**U**[10]
Gross Fixed Capital Formation - HP (1988.1-2006.2)	**0.216**	U	0.165	u	**0.497**	**U**[11]	0.195	u[10]
Trade Activity (Imports+Exports) - HP (1988.1-2006.2)	**0.430**	U	**0.536**	**U**	**0.274**	(U)[4]	0.014	u[12]
Stock Market Index - Return[h] (1990.2-2006.11)	**-0.143**[g]	D	**-0.159**[g]	D	-0.086	d	-0.066	d[13]

EU: AT, BE, DE, DK, ES, FI, FR, GR, IT, NE, UK. **EMU**: AT, BE, DE, ES, FI, FR, GR, IT, NE. **Core EU**: DE, ES, FR, IT, UK. **Core EMU**: DE, ES, FR, IT. **Non-Core EU**: AT, BE, DK, FI, GR, NE. **Non-Core EMU**: AT, BE, FI, GR, NE. **DM Bloc + Finland**: AT, BE, DE, DK, FI, NE. **NAFTA**: CA, MEX, USA. **Note**: Finland was not formally part of the Deutsche Marc (DM) Bloc. In computing global indices, however, we include it for its geographical proximity to the countries in the Bloc within the borders of the EU.

Breakpoint Date (Europe, Quarterly Data): 1998.4. **Breakpoint Date (Europe, Monthly Data)**: 1998.12. **Breakpoint Date (NAFTA, Quarterly Data)**: 1993.4. **Breakpoint Date (NAFTA, Monthly Data)**: 1993.12.

Bootstrap Replications: 1500. **Bootstrap Iterations**: 750.

[a]Does not include: AT, FI, GR. [b]Does not include: AT. [c]Also includes: IE, LUX, PT, SE. [d]Also includes: IE, LUX, PT. [e]Does not include: IT. Includes: IE. [f]Does not include: IT. [g] Also includes: IE. [h]Monthly data.

[1]1991.4-2006.3. [2]1991.2-2006.3. [3]1991.1-2007.1. (4)1991.1-2006.3. [5]1987.8-2006.11. [6]1980.4-2006.3. [7] 1980.2-2006.3 [8]1980.2-2007.1. [9]1991.2-2007.1. [10]1980.1-2006.4. [11]1991.1-2006.2. [12]1981.1-2006.3. [13]1983.2-2006.11.

Symbols and Notation. u: non-significantly positive correlation change; U: positive correlation change (significant at 10% level); **U** positive correlation change (significant at 5% level); d: non-significantly negative correlation change; D: negative correlation change (significant at 10% level); **D**: negative correlation change (significant at 5% level). **Entries in parentheses**: bias-correction is applied. **Correlation Changes in bold**: significant at either 5% or 10% level.

Table 2b. Weighted Average Correlation Changes (WACCs) (2)

EU15 - Detrended Real GDP - HPMV (KF)

	AT	BE	DE	DK	ES	FI	FR	GR	IT	NE	SE	UK
AT	--											
BE	u	--										
DE	u	u	--									
DK	**(U)**	**U**	u	--								
ES	u	u	U	u	--							
FI	**U**	u	u	**U**	u	--						
FR	u	u	u	u	u	u	--					
GR	d	d	u	d	d	d	u	--				
IT	u	d	**U**	u	u	u	u	u	--			
NE	**U**	u	**U**	**U**	u	**U**	u	d	u	--		
SE	u	u	**U**	U	u	u	u	d	d	u	--	
UK	**U**	**U**	u	d	u	u	**U**	d	u	u	u	--

		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%

	AT	BE	DE	DK	ES	FI	FR	GR	IT	NE	SE	UK
AT	0.000											
BE	0.593	0.000										
DE	0.346	0.307	0.000									
DK	**1.368**	**0.794**	0.128	0.000								
ES	0.450	0.098	**0.653**	0.322	0.000							
FI	**1.333**	0.328	0.827	**0.643**	0.099	0.000						
FR	0.256	0.072	0.691	0.574	0.216	0.180	0.000					
GR	-0.346	-0.126	0.089	-0.380	-0.081	-0.208	0.236	0.000				
IT	0.364	-0.119	**0.578**	0.267	0.105	0.068	0.197	0.179	0.000			
NE	**0.529**	0.398	**0.695**	**0.641**	0.158	**0.528**	0.360	-0.422	0.077	0.000		
SE	0.293	0.162	**0.607**	**0.721**	0.032	0.167	0.185	-0.406	-0.229	0.309	0.000	
UK	**1.319**	**0.667**	0.547	-0.120	0.080	0.051	**0.646**	-0.086	0.197	0.336	0.615	0.000

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.

Symbols and Notation. u: non-significantly positive correlation change; U: positive correlation change (significant at 10% level); **U**: positive correlation change (significant at 5% level); d: non-significantly negative correlation change; D: negative correlation change (significant at 10% level); **D**: negative correlation change (significant at 5% level). **Entries in parentheses**: bias-correction is applied. **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 - Detrended Real GDP, HPMV (Kalman Filter) - Pairwise Correlation Changes

EU15 - Detrended Real GDP - Production Function (1)

	BE	DE	DK	ES	FR	GR	IT	NE	UK
BE	--								
DE	u	--							
DK	u	**U**	--						
ES	d	U	**U**						
FR	d	u	U	u	--				
GR	D	d	d	d	d	--			
IT	d	**U**	**U**	u	u	u	--		
NE	u	d	**U**	U	u	d	u	--	
UK	d	**U**	u	u	**U**	u	u	u	--

		UP	Sign. UP	DOWN	Sign. DOWN	Total
EU15	**#**	15	**10**	10	**1**	36
	%	41.7%	**27.8%**	27.8%	**2.8%**	100.0%
EMU12	**#**	9	**3**	8	**1**	21
	%	42.9%	**14.3%**	38.1%	**4.8%**	100.0%

	BE	DE	DK	ES	FR	GR	IT	NE	UK
BE	0.000								
DE	0.460	0.000							
DK	0.439	**1.541**	0.000						
ES	-0.307	**0.801**	**0.647**						
FR	-0.091	0.362	**0.885**	0.045	0.000				
GR	**-0.406**	0.049	-0.001	-0.157	-0.016	0.000			
IT	-0.264	**0.765**	**0.726**	0.044	0.126	0.014	0.000		
NE	0.316	-0.085	**1.404**	**0.485**	0.110	-0.300	0.441	0.000	
UK	-0.034	**1.533**	0.300	0.210	**0.532**	0.194	0.355	0.780	0.000

Samples (Quarterly Data). BE: 1983.2-2006.2; DE: 1991.4-2006.2; DK: 1983.2-2006.2; ES: 1986.2-2006.2; FR: 1983.2-2006.2; GR: 1983.2-2006.2; IT: 1983.2-2006.2; NE: 1983.2-2006.2; UK: 1983.2-2006.2.

Breakpoint Date: 1998.4.

Symbols and Notation. u: non-significantly positive correlation change; U: positive correlation change (significant at 10% level); **U**: positive correlation change (significant at 5% level); d: non-significantly negative correlation change; D: negative correlation change (significant at 10% level); **D**: negative correlation change (significant at 5% level). **Entries in parentheses**: bias-correction is applied. **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 - Detrended Real GDP, Production Function (1) - Pairwise Correlation Changes

Detrended Real GDP

A - HPMV (KF)

		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%

B - HPMV (KS)

		UP	Sign. UP	DOWN	Sign. DOWN	Total
EU15	#	33	**15**	15	**3**	66
	%	50.0%	**22.7%**	22.7%	**4.5%**	100.0%
EMU12	#	22	**4**	8	**2**	36
	%	61.1%	**11.1%**	22.2%	**5.6%**	100.0%

C - Production Function (1)

		UP	Sign. UP	DOWN	Sign. DOWN	Total
EU15	#	15	**10**	10	**1**	36
	%	41.7%	**27.8%**	27.8%	**2.8%**	100.0%
EMU12	#	9	**3**	8	**1**	21
	%	42.9%	**14.3%**	38.1%	**4.8%**	100.0%

D - Production Function (2)

		UP	Sign. UP	DOWN	Sign. DOWN	Total
EU15	#	16	**6**	13	**1**	36
	%	44.4%	**16.7%**	36.1%	**2.8%**	100.0%
EMU12	#	7	**2**	11	**1**	21
	%	33.3%	**9.5%**	52.4%	**4.8%**	100.0%

E - HPMV (KF)

		UP	Sign. UP	DOWN	Sign. DOWN	Total
EU15	#	22	**7**	7	**0**	36
	%	61.1%	**19.4%**	19.4%	**0.0%**	100.0%
EMU12	#	14	**3**	4	**0**	21
	%	66.7%	**14.3%**	19.0%	**0.0%**	100.0%

F - HPMV (KS)

		UP	Sign. UP	DOWN	Sign. DOWN	Total
EU15	#	19	**6**	8	**3**	36
	%	52.8%	**16.7%**	22.2%	**8.3%**	100.0%
EMU12	#	13	**0**	6	**2**	21
	%	61.9%	**0.0%**	28.6%	**9.5%**	100.0%

Symbols and Notation. #: 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.

Notes: The six panels summarize inference on pairwise correlation changes between real GDPs, detrended using the techniques described in the paper. Panels A and B report summary figures for the same sample of countries as in Table 3. Panels C, D, E, and F report summary figures for the same sample of countries as in Table 4. **HMPV (KF)**: Multivariate HP Filter (Kalman Filter); **HMPV (KS)**: Multivariate HP Filter (Kalman Smoother).

Table 5. EU15 - Detrended Real GDP, Filter Comparison - Pairwise Correlation Changes

EU15 - Real GDP - Growth

	AT	BE	DE	DK	ES	FI	FR	GR	IT	NE	SE	UK
AT	--											
BE	u	--										
DE	u	d	--									
DK	**U**	u	u	--								
ES	u	d	d	u	--							
FI	u	u	u	d	u	--						
FR	d	u	u	u	u	d	--					
GR	d	**D**	d	d	d	u	d	--				
IT	d	u	U	u	u	u	u	d	--			
NE	**U**	u	u	**U**	d	u	u	d	**U**	--		
SE	U	u	**U**	u	d	u	d	d	d	U	--	
UK	u	u	u	d	u	d	**U**	d	**U**	d	u	--

		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%

	AT	BE	DE	DK	ES	FI	FR	GR	IT	NE	SE	UK
AT	0.000											
BE	0.118	0.000										
DE	0.148	-0.024	0.000									
DK	**0.506**	0.005	0.035	0.000								
ES	0.015	-0.322	-0.006	0.089	0.000							
FI	0.256	0.235	0.191	-0.067	0.090	0.000						
FR	-0.268	0.034	0.055	0.102	0.075	-0.057	0.000					
GR	-0.053	**-0.388**	-0.263	-0.121	-0.246	0.032	-0.188	0.000				
IT	-0.071	0.189	**0.525**	0.135	0.242	0.270	0.217	-0.241	0.000			
NE	**0.314**	0.086	0.099	**0.359**	-0.049	0.092	0.278	-0.186	**0.444**	0.000		
SE	**0.369**	0.162	**0.650**	0.489	-0.229	0.220	-0.095	-0.270	-0.198	**0.534**	0.000	
UK	0.308	0.125	0.182	-0.063	0.238	-0.104	**0.306**	-0.098	**0.411**	-0.123	0.124	0.000

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. u: non-significantly positive correlation change; U: positive correlation change (significant at 10% level); **U**: positive correlation change (significant at 5% level); d: non-significantly negative correlation change; D: negative correlation change (significant at 10% level); **D**: negative correlation change (significant at 5% level). **Entries in parentheses**: bias-correction is applied. **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 6. EU15 - Real GDP, Growth - Pairwise Correlation Changes

EU15 - Industrial Production Index - Growth

	AT	BE	DE	DK	ES	FI	FR	GR	IE	IT	LUX	NE	PT	SE	UK
AT	--														
BE	**U**	--													
DE	u	u	--												
DK	u	u	d	--											
ES	d	u	u	u	--										
FI	u	u	u	d	U	--									
FR	u	u	d	u	u	**U**	--								
GR	u	u	U	d	(U)	u	u	--							
IE	u	u	**U**	u	d	u	U	u	--						
IT	u	**U**	u	U	u	u	u	u	d	--					
LUX	d	d	D	U	**D**	u	D	d	d	d	--				
NE	u	u	d	u	d	**U**	u	d	d	**U**	d	--			
PT	u	d	d	u	d	u	d	d	u	**D**	u	d	--		
SE	u	u	u	u	u	u	u	**U**	u	U	u	u	d	--	
UK	u	u	u	u	U	u	**U**	(U)	u	**U**	u	u	d	u	--

	AT	BE	DE	DK	ES	FI	FR	GR	IE	IT	LUX	NE	PT	SE	UK
AT	0.000														
BE	**0.369**	0.000													
DE	0.088	0.225	0.000												
DK	0.389	0.112	-0.058	0.000											
ES	-0.045	0.231	0.165	0.025	0.000										
FI	0.380	0.217	0.289	-0.004	**0.329**	0.000									
FR	0.187	0.213	-0.074	0.009	0.021	**0.465**	0.000								
GR	0.004	0.284	**0.382**	-0.063	**0.434**	0.290	0.131	0.000							
IE	0.174	0.139	**0.442**	0.008	-0.102	0.097	**0.198**	0.319	0.000						
IT	0.105	**0.508**	0.278	**0.227**	0.120	0.316	0.132	0.335	-0.005	0.000					
LUX	-0.019	-0.034	**-0.360**	**0.239**	**-0.388**	0.096	**-0.215**	-0.133	-0.057	-0.058	0.000				
NE	0.005	0.228	-0.018	0.326	-0.036	**0.374**	0.101	-0.014	-0.034	**0.355**	-0.030	0.000			
PT	0.016	-0.151	-0.195	0.122	-0.475	0.037	-0.097	-0.398	0.128	**-0.301**	0.091	-0.288	0.000		
SE	0.219	0.149	0.250	0.133	0.259	0.251	0.055	**0.779**	0.131	**0.435**	0.176	0.027	-0.009	0.000	
UK	0.287	0.352	0.217	0.230	**0.393**	0.322	**0.350**	**0.434**	0.088	**0.506**	0.043	0.222	-0.079	0.214	0.000

		UP	Sign. UP	DOWN	Sign. DOWN	Total
EU15	**#**	58	**18**	25	**4**	105
	%	55.2%	**17.1%**	23.8%	**3.8%**	100.0%
EMU12	**#**	32	**10**	20	**4**	66
	%	48.5%	**15.2%**	30.3%	**6.1%**	100.0%

Samples (Quarterly Data). ***Industrial Production Index*** . AT: 1980.1-2007.1; BE: 1980.1-2007.1; DE: 1980.1-2007.1; DK: 1980.1-2007.1; ES: 1980.1-2007.1; IE: 1980.1-2007.1; IT: 1980.1-2007.1; FI: 1980.1-2007.1; FR: 1980.1-2007.1; GR: 1980.1-2007.1; LUX: 1980.1-2007.1; NE: 1980.1-2007.1; PT: 1980.1-2007.1; SE: 1980.1-2007.1; UK: 1980.1-2007.1.

Breakpoint Date: 1998.4.

Symbols and Notation. u: non-significantly positive correlation change; U: positive correlation change (significant at 10% level); **U**: positive correlation change (significant at 5% level); d: non-significantly negative correlation change; D: negative correlation change (significant at 10% level); **D**: negative correlation change (significant at 5% level). **Entries in parentheses**: bias-correction is applied. **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 7. EU15 - Industrial Production Index, Growth - Pairwise Correlation Changes

EU15 - Detrended Final Consumption Expenditure - HP

	AT	BE	DE	DK	ES	FI	FR	GR	IT	NE	SE	UK
AT	--											
BE	u	--										
DE	u	u	--									
DK	u	d	d	--								
ES	u	d	u	u	--							
FI	u	D	u	u	**D**	--						
FR	u	u	u	d	u	D	--					
GR	u	d	d	u	d	**D**	u	--				
IT	u	u	u	u	d	d	u	d	--			
NE	u	u	**U**	d	d	d	u	D	u	--		
SE	(U)	**U**	u	u	(U)	**U**	u	u	**U**	u	--	
UK	u	u	u	d	u	**D**	u	d	u	d	u	--

	AT	BE	DE	DK	ES	FI	FR	GR	IT	NE	SE	UK
AT	0.000											
BE	0.077	0.000										
DE	0.072	0.264	0.000									
DK	0.272	-0.343	-0.106	0.000								
ES	0.385	-0.140	0.317	0.600	0.000							
FI	0.021	**-0.564**	0.140	0.221	**-0.576**	0.000						
FR	0.173	0.151	0.028	-0.025	0.071	**-0.626**	0.000					
GR	0.009	-0.009	-0.088	0.140	-0.186	**-0.628**	0.149	0.000				
IT	0.117	0.033	0.550	0.020	-0.088	-0.087	0.034	**-0.275**	0.000			
NE	0.043	0.282	**0.641**	-0.478	-0.107	-0.104	0.116	-0.343	0.481	0.000		
SE	**0.769**	**1.069**	0.455	0.417	**0.892**	**1.114**	0.095	0.318	**0.702**	0.254	0.000	
UK	0.502	0.284	0.146	-0.403	0.039	**-0.621**	0.313	-0.092	0.259	-0.351	0.364	0.000

		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.

Symbols and Notation. u: non-significantly positive correlation change; U: positive correlation change (significant at 10% level); **U**: positive correlation change (significant at 5% level); d: non-significantly negative correlation change; D: negative correlation change (significant at 10% level); **D**: negative correlation change (significant at 5% level). **Entries in parentheses**: bias-correction is applied. **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 8. EU15 - Detrended Final Consumption Expenditure, HP Filter - Pairwise Correlation Changes

EU15 - Detrended Gross Fixed Capital Formation - HP

	AT	BE	DE	DK	ES	FI	FR	GR	IT	NE	SE	UK
AT	--											
BE	u	--										
DE	**U**	u	--									
DK	**U**	u	U	--								
ES	u	u	U	u	--							
FI	U	d	**U**	u	d	--						
FR	u	u	U	U	d	u	--					
GR	U	d	u	d	d	d	d	--				
IT	d	d	d	u	**D**	d	d	d	--			
NE	**U**	u	**U**	U	**U**	**U**	U	D	d	--		
SE	u	**U**	u	u	u	u	u	d	d	**U**	--	
UK	u	d	u	d	u	d	u	d	u	u	**(U)**	--

		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%

	AT	BE	DE	DK	ES	FI	FR	GR	IT	NE	SE	UK
AT	0.000											
BE	0.294	0.000										
DE	**0.292**	0.579	0.000									
DK	**0.926**	0.368	**0.463**	0.000								
ES	0.432	0.097	**0.445**	0.396	0.000							
FI	**0.850**	-0.053	**0.824**	0.459	-0.010	0.000						
FR	0.335	0.018	**0.340**	**0.585**	-0.058	0.172	0.000					
GR	**0.339**	-0.401	0.164	-0.286	-0.138	-0.029	-0.124	0.000				
IT	-0.116	-0.387	-0.114	0.111	**-0.649**	-0.636	-0.466	-0.329	0.000			
NE	**0.655**	0.277	**0.455**	**0.364**	**0.584**	**0.549**	**0.531**	**-0.302**	-0.305	0.000		
SE	0.553	**1.266**	0.651	0.621	0.391	0.765	0.019	-0.075	-0.298	**1.018**	0.000	
UK	0.217	-0.074	0.387	-0.170	0.269	-0.012	0.083	-0.049	0.083	0.254	**0.581**	0.000

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. u: non-significantly positive correlation change; U: positive correlation change (significant at 10% level); **U**: positive correlation change (significant at 5% level); d: non-significantly negative correlation change; D: negative correlation change (significant at 10% level); **D**: negative correlation change (significant at 5% level). **Entries in parentheses**: bias-correction is applied. **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 9. EU15 - Detrended Gross Fixed Capital Formation, HP Filter - Pairwise Correlation Changes

NAFTA

Business Cycle Measure	Filtering Method	CA-MEX	CA-USA	MEX-USA
Real GDP	HPUV (KF)	0.169 u	-0.161 d	**0.724 U**
	HPMV (KF)	0.085 u	-0.164 d	**0.566 U**
	Growth	**-0.169** D	-0.237 d	0.140 u
Industrial Production Index	Growth	0.154 u	-0.130 d	0.160 u
Final Consumption Expenditure	HP	**0.730 U**	0.043 u	**0.965 U**
Gross Fixed Capital Formation	HP	**0.485** U	0.103 u	0.239 u
Stock Market Index	Return[(a)]	**0.328** U	-0.064 d	-0.114 d
Trade Activity	HP	0.050 u	-0.023 d	0.046 u

PCC between	Filtering Method	CA	MEX	USA
Stock Market Index and Real GDP	HP	0.374 u	**0.649 U**	0.452 u
Trade Activity and Real GDP	HP	0.004 u	**0.240** U	0.045 u

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. ***Industrial Production Index***. CA: 1980.1-2007.1; MEX: 1980.2-2007.1; USA: 1980.1-2007.1. ***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. ***Stock Market Index***. CA: 1982.1-2006.3; MEX: 1983.1-2006.3; USA: 1974.2-
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. u: non-significantly positive correlation change; U: positive correlation change (significant at 10% level); **U**: positive correlation change (significant at 5% level); d: non-significantly negative correlation change; D: negative correlation change (significant at 10% level); **D**: negative correlation change (significant at 5% level). **Entries in parentheses**: bias-correction is applied. **Correlation Changes in bold**: significant at either 5% or 10% level.

Table 10. NAFTA - All Measures - Pairwise Correlation Changes

EU15 - Detrended Trade Activity - HP

	AT	BE	DE	DK	ES	FI	FR	GR	IT	NE	SE	UK
AT	--											
BE	u	--										
DE	d	u	--									
DK	u	u	u	--								
ES	u	u	d	u	--							
FI	**U**	u	**(U)**	**U**	(U)	--						
FR	u	u	u	**U**	u	**U**	--					
GR	u	**U**	u	u	**(U)**	U	u	--				
IT	u	u	u	u	u	**(U)**	U	u	--			
NE	U	**(U)**	u	u	u	**U**	U	**U**	u	--		
SE	u	u	u	u	u	u	d	**U**	u	u	--	
UK	u	u	u	**U**	u	u	**U**	u	u	u	u	--

	AT	BE	DE	DK	ES	FI	FR	GR	IT	NE	SE	UK
AT	0.000											
BE	0.210	0.000										
DE	-0.012	0.164	0.000									
DK	0.217	0.150	0.125	0.000								
ES	0.083	0.457	-0.058	0.277	0.000							
FI	**0.804**	0.376	**0.936**	**0.661**	**0.516**	0.000						
FR	0.099	0.095	0.066	**0.290**	0.106	**0.558**	0.000					
GR	0.461	**0.848**	0.145	0.081	**0.498**	**0.535**	0.381	0.000				
IT	0.217	0.301	0.264	0.246	0.261	**0.413**	**0.207**	0.313	0.000			
NE	**0.331**	**0.539**	0.033	0.180	0.403	**0.831**	**0.340**	**0.493**	0.372	0.000		
SE	0.126	0.099	0.231	0.027	0.209	0.073	-0.083	**0.691**	0.063	0.157	0.000	
UK	0.490	0.014	0.666	**0.476**	0.265	0.259	**0.388**	0.231	0.146	0.341	0.477	0.000

		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.

Symbols and Notation. u: non-significantly positive correlation change; U: positive correlation change (significant at 10% level); **U**: positive correlation change (significant at 5% level); d: non-significantly negative correlation change; D: negative correlation change (significant at 10% level); **D**: negative correlation change (significant at 5% level). **Entries in parentheses**: bias-correction is applied. **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 11. EU15 - Detrended Trade Activity, HP Filter - Pairwise Correlation Changes

EU15 - Stock Market Index - Monthly Return

	AT	BE	DE	DK	ES	FI	FR	GR	IE	IT	NE	PT	UK
AT	--												
BE	d	--											
DE	**D**	d	--										
DK	d	d	u	--									
ES	d	d	U	d	--								
FI	**D**	**D**	u	d	u	--							
FR	d	d	**U**	u	u	**U**	--						
GR	d	d	d	d	d	d	u	--					
IE	d	d	u	d	d	D	d	d	--				
IT	D	d	u	d	d	d	U	d	d	--			
NE	d	d	u	u	u	u	**U**	d	d	u	--		
PT	**D**	d	u	d	u	u	u	d	d	d	d	--	
UK	u	u	U	u	u	u	u	u	d	u	U	d	--

	AT	BE	DE	DK	ES	FI	FR	GR	IE	IT	NE	PT	UK
AT	0.000												
BE	-0.062	0.000											
DE	**-0.246**	-0.165	0.000										
DK	-0.180	-0.036	0.065	0.000									
ES	-0.148	-0.206	**0.116**	-0.050	0.000								
FI	**-0.354**	**-0.372**	0.140	-0.179	0.014	0.000							
FR	-0.194	-0.194	**0.111**	0.150	0.094	**0.249**	0.000						
GR	-0.185	-0.159	-0.038	-0.192	-0.031	-0.003	0.012	0.000					
IE	-0.065	-0.143	0.083	-0.122	-0.160	**-0.235**	-0.050	-0.123	0.000				
IT	**-0.371**	-0.227	0.143	-0.133	-0.017	-0.051	**0.128**	-0.203	-0.172	0.000			
NE	-0.104	-0.117	0.098	0.056	0.021	0.055	**0.099**	-0.011	-0.026	0.035	0.000		
PT	**-0.474**	-0.244	0.046	-0.100	0.027	0.017	0.004	-0.273	-0.263	-0.009	-0.133	0.000	
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	0.000

		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. u: non-significantly positive correlation change; U: positive correlation change (significant at 10% level); **U**: positive correlation change (significant at 5% level); d: non-significantly negative correlation change; D: negative correlation change (significant at 10% level); **D**: negative correlation change (significant at 5% level). **Entries in parentheses**: bias-correction is applied. **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 12. EU15 - Stock Market Index, Monthly Return - Pairwise Correlation Changes

HONG KONG - USA

Business Cycle Measure	Filtering Method	HK-USA	
Real GDP	HPMV (KF)	**-0.519**	**(D)**
	Growth	0.015	u
Final Consumption Expenditure	HP	**-0.585**	**D**
Gross Fixed Capital Formation	HP	-0.629	d
Stock Market Index	Return[(a)]	-0.022	d
Trade Activity	HP	-0.192	d

PCC between	Filtering Method	HK	
Stock Market Index and Real GDP	HP	0.142	u
Trade Activity and Real GDP	HP	0.218	u

Samples (Quarterly Data). ***Real GDP*** : 1975.4-2006.3 (HPMV), 1974.2-2006.3 (Growth). ***Final Consumption Expenditure, Gross Fixed Capital Formation*** : 1973.1-2006.4. ***Trade Activity*** : 1973.1-2006.3. ***Stock*** **Samples (Monthly Data)**. ***Stock Market Index*** : 1974.7-2006.11.

Breakpoint Date (Quarterly Data): 1983.3. **Breakpoint Date (Monthly Data)**: 1983.9.

[(a)]Monthly Data.

Symbols and Notation. u: non-significantly positive correlation change; U: positive correlation change (significant at 10% level); **U** positive correlation change (significant at 5% level); d: non-significantly negative correlation change; D: negative correlation change (significant at 10% level); **D**: negative correlation change (significant at 5% level). **Entries in parentheses**: bias-correction is applied. **Correlation Changes in bold**: significant at either 5% or 10% level.

Table 13. Hong Kong/USA - All Measures - 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 14a. Monte Carlo Experiments (1)

Bootstrap Type	Simulated Data "True" Statistics		Monte Carlo Experiment 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 14b. Monte Carlo Experiments (2)

Bootstrap Type	Great Moderation Parameters		Monte Carlo Experiment Coverage Probability	
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 14c. Monte Carlo Experiments (3)