Structural Breaks in International Inflation Linkages for OECD Countries

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Abstract

This paper studies the link between domestic inflation for 19 OECD countries and a corresponding country-specific global inflation series. This is achieved through an iterative methodology, which iterates between coefficient and variance tests, while taking account of outliers. This procedure is applied to both univariate and bivariate inflation models that relate domestic and global inflation, with the latter is calculated as a trade-weighted average of inflation in a country's trading partners. The empirical analysis uses monthly consumer price inflation over 1970 to 2010 and the following key results emerge. First, the univariate analysis yields breaks in the conditional mean that are broadly consistent with the existing literature. Second, we document clusters of variance breaks occuring around the mid 1970s, early 1980s and early 1990s, casting doubt on the claim in the literature that changes of the inflation has been mainly in the mean. Third, bivariate models show a positive and strengthening contemporaneous relationship between domestic and country specific global inflation. Although the dates and extent of change vary over countries, our results imply increased co-movements of infation, particularly during the 1980s and 1990s. Fourth, we demonstrate that the above results crucially depend on an appropriate treatment of outliers.

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A detailed analysis of change in international inflation linkages by employing

1 Introduction

Over the last decade or so, policymakers and researchers have documented and discussed the globalization of inflation, namely the apparently strong co-movement of inflation seen over the last two decades or more. Indeed, even in the context of the large economies of the US and Euro area, Bernanke (2007) and Trichet (2008), respectively, emphasize that their central banks now need to monitor carefully international price developments and analyze their implications for the domestic economy. The strong link between domestic inflation and the international environment is also recognized in the models of Pesaran et al. (2004); Ciccarelli and Mojon (2010); Mumtaz and Surico (2012) and many others. However, Bataa et al. (2013b) is, to our knowledge, the only paper that attempts to pin down the nature and dates of change in international inflation linkages between specific countries.

Studies of the globalization of inflation predominantly employ factor analysis to extract a common international inflation component. Changes in co-movement in relation to this factor are then studied for individual countries, using either subsample analysis or allowing for random coefficient variation (see Ciccarelli and Mojon, 2010; Monacelli and Sala, 2009; Mumtaz and Surico, 2012; Neely and Rapach, 2011). Nevertheless, implicit and untested assumptions about parameter constancy are required in order to extract the factor(s), and changing covariances could make these unreliable. This is established in a univariate context by Pitarakis (2004), who shows that serious size distortions arise in testing for mean (and/or persistence) change when volatility is assumed to be stable but is, in fact, subject to breaks.

This paper studies the globalization of inflation by applying an iterative structural break testing methodology to model the link be-

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tween domestic and country-specific foreign inflation. While the multiple break testing methodology of Bai and Perron (1998) provides the basic building block, our procedure allows the possibility of distinct changes in the model coefficients and in volatility. Not only does the presence of volatility breaks affect inference on coefficients, as shown by Pitarakis (2004), but inference on volatility breaks can be misleading if the computed residuals are contaminated by un-modeled mean breaks (Sensier and van Dijk, 2004). Further, ignoring the presence of outliers can lead to misspecification and biases in estimated parameters (see, among others, Giordani et al., 2007; Chen and Liu, 1993). Therefore, to avoid these problems, breaks in the conditional mean and variance parameters are identified by iterating between mean and variance tests, with outliers also identified in relation to conditional mean and volatility regimes. This methodology is closely related to, and builds upon, that of Bataa et al. (2013b,a).

In these models, country-specific foreign inflation is constructed as the bilateral trade weighted average of inflation in all other countries in our sample and is treated as weakly exogenous. As a preliminary step to the bivariate[1] inflation models linking domestic and foreign inflation, univariate inflation models are employed to examine the stability of domestic inflation and to assess the robustness of existing univariate findings. Although there is a substantial literature on breaks in univariate inflation models, including Cecchetti and Debelle (2006); O'Reilly and Whelan (2005); Levin and Piger (2003); Bataa et al. (2013a), the tests applied in almost all papers make the unrealistic assumption that the variance of inflation is constant over time. Our main focus, however, is analyzing changes in the linkage of domestic with international monthly CPI inflation for 19 OECD countries over

[1] All the models in this paper are single equation models. In other words, we use the term "bivariate model" to refer to the model that shows the relationships between two variables, namely domestic and foreign inflation, where their lagged and contemporaneous terms are also allowed.

the period January 1970 to September 2010.

Our main findings can be summarized as follows. Firstly, univariate inflation models yield inference on breaks in the conditional mean that are broadly consistent with the existing literature. However, the number of conditional mean (that is, intercept and/or dynamic) breaks found in our analysis is fewer compared to other studies (see Bataa et al., 2013a; Cecchetti and Debelle, 2006). Secondly, we document clusters of variance breaks occurring around the mid 1970s, early 1980s and early 1990s, while only clusters of mean breaks have been widely documented in the previous literature. These variance breaks typically reflect substantial declines in the volatility of inflation, casting doubt on the common claim in the literature that changes of inflation have been mainly in the mean. Thirdly, examining bivariate inflation models, we find a positive and strengthening contemporaneous relationship between domestic and country specific foreign inflation. Furthermore, the timing of break dates in conditional means and variances, identified using bivariate inflation models, also exhibit a clustering pattern around the mid 1970s, early to mid 1980s and early 1990s, suggesting commonality in changes to international inflation linkages. These bivariate inflation models also confirm a general pattern of declining persistence of domestic inflation.

The rest of the paper is organized as follows. Section 2 describes our methodology, including our iterative procedure for structural break detection. Section 3 then presents the data and section 4 reports the results of both the univariate and bivariate inflation analyses. A sensitivity analysis is presented in section 5 and section 6 concludes.

2 Methodology

2.1 Iterative methodology of structural break analysis

As a complement to the existing literature that often conducts break point tests under misspecification (omitting changes in either mean or variance of a time series), we employ an iterative approach which aims to avoid misspecification through the use of an iterative procedure. Our research adapts the iterative methodology by Bataa et al. (2013a,b) to analyze structural breaks in the mean, persistence (dynamics) and innovation variance (volatility) of univariate inflation series.

The iterative methodology proposed by Bataa et al. (2013a) tests for structural breaks in each of the components of inflation: seasonal, mean, dynamics and volatility one at a time conditional on previously found breaks in all other components. The testing procedure employed is that of Qu and Perron (2007), together with the outlier detection and removal procedure of Stock and Watson (2003). However, this procedure is quite complex and, as indicated by the Monte Carlo results in Bataa et al. (2013b) for the multivariate case, iteration is relatively unimportant in practice for the variance component. Further, their separation of mean and dynamics breaks can have relatively poor performance in practice, especially since the initial tests for mean breaks apply Heteroskedasticity and Autocorrelation robust (HAC) inference using the approach of Andrews (1991), which is known to be sometimes badly oversized (Bai and Perron, 2006). Finally, while their outlier detection procedure makes use of detected coefficient breaks, variance breaks are ignored for outlier detection. Therefore, we propose a simple, yet efficient version of the iterative approach of Bataa et al. (2013a) that also takes account of these concerns. It is more flexible in a number of respects, including re-specification of the model employed at each iteration, reflecting the effects of detecting and removing outliers.

Note that seasonality is not a particular focus of interest in this study. Since CPI data are typically available only in a seasonally unadjusted form, we use the widely applied X-12-ARIMA seasonal adjustment procedure to deseasonalize the data prior to beginning our iterative procedure. The X-12-ARIMA procedure is particularly suitable in our context, as it allows for the presence of trend, deterministic seasonal patterns, holidays and trading day adjustment, additive outliers and level shifts (Osborn and Ghysels, 2001, p.106-127). Note, however, that while additive outliers are taken into account for the purposes of seasonal adjustment, they remain in the series after seasonal factors are removed (Census Bureau, 2011, p.123-127).

Here the discussion of methodology focuses on univariate inflation models although this paper concerns changing dynamics in international links. This is because many studies are readily available in the context of univariate inflation and results from these studies can be compared to that of ours after applying the iterative testing procedure. In subsection 2.3, we will turn to the analysis of international inflation links.

A time-varying univariate AR model for monthly domestic inflation in a country, π_t^D, is given by

$$\pi_t^D = \mu_j + \sum_{i=1}^{n} \alpha_{ij} \pi_{t-i}^D + \upsilon_t, \tag{1}$$

where the subscript j indicates the coefficient regime and υ_t is a zero mean uncorrelated process whose variance $\sigma_k^2 = E[\upsilon_t^2]$ is allowed to change over variance regimes (indicated by the subscript k). Our interest, therefore, focuses on possible discrete breaks in the coefficients and the disturbance variance, while allowing for the presence of additive outliers in π_t^D, which could be due to (say) changes in indirect taxes.

Denote m as the unknown number of coefficient breaks. Within each of $m+1$ coefficient regimes, $\delta_j = (\mu_j, \alpha_{1j}, \ldots, \alpha_{nj})'$ is time-invariant and all AR roots are assumed to lie strictly outside the unit circle. The j^{th} regime extends over observations $t = T_{j-1}+1, \ldots, T_j$ using the convention that $T_0 = 0$ and $T_{m+1} = T$. All coefficients are allowed to change and the break dates $(T_1, \ldots, T_m)$ are treated as unknown. Similarly, σ_k^2 is constant within each volatility regime and is assumed to be conditionally homoskedastic. Our iterative approach to specifying the model in (1) is given by the following steps.

Step 1 - Outlier detection: The first iteration starts by identifying outliers in the deseasonalized full sample of data. Employing the outlier detection procedure by Stock and Watson (2003), outliers are defined as four times of the interquartile range from the median[2]. Detected outliers are replaced by the median of the six neighboring non outlier values.

Step 1* - Outlier detection for subsequent iterations: In subsequent iterations, outliers are examined separately within each coefficient regime and in data adjusted for volatility breaks (by standardizing the series using standard deviations of residuals in corresponding volatility regimes). Detected outliers are replaced by the median of the six neighboring non outlier standardized values. The data are then destandardized, to yield a series adjusted only for outliers.

Step 2 - Model selection: A univariate inflation model is selected using the Schwartz Information Criterion (thereafter SIC). Specifically, using the AR model and allowing a maximum lag of $n = 17$,

[2]There is a trade-off for choosing between too small or too big number to multiply the interquartile range. If the number is chosen too large, then it is unable to pick up obvious outliers. If it is chosen too small, too many outliers are detected in a single series. In our judgment a value of four times the interquartile range seems appropriate for most inflation series as it allows obvious outliers to be identified and results in a reasonably small number of outliers.

all possible combinations of lags are considered, implying a total of 2^{17} models. Since "gaps" are permitted in coefficients, i is not necessarily consecutive in (1). To ensure comparability, all models for a given country are estimated over a common set of data, and the choice among them is made based on minimum SIC. Persistence is measured by the sum of autoregressive coefficients, $\hat{\rho} = \sum_{i=1}^{n} \hat{\alpha}_i$, as it is the best scalar measure of the persistence, as indicated by Andrews and Chen (1994).

Step 3 - Preliminary coefficient break test: After having specified lags in (1), the Bai and Perron (1998) multiple structural breaks procedure is applied to the coefficient vector of the autoregressive model (including intercept and slope parameters of the regression). The possibility of heteroskedasticity in the variance is allowed by employing Heteroskedasticity Consistent (HC) inference[3]. Although HC inference can lead to oversized coefficient break tests when there is no heteroskedasticity, shown by the simulation analysis by Bai and Perron (2006), the estimates in each regime are consistent in a large sample. Further, coefficient breaks identified here are reconsidered in step 5 of the iteration.

Step 4 - Variance break test: Conditional on the coefficient break dates from step 3, variance breaks are examined through tests applied to the mean of the squared residuals (see section 2.2 for details). This is to mitigate the concern of misleading inference of variance breaks, caused by obtained residuals that may be contaminated by coefficient breaks (Sensier and van Dijk, 2004; Pitarakis, 2004).

Step 5 - Coefficient break test: To avoid the serious problems for coefficient break tests of omitted variance breaks (Pitarakis, 2004),

[3]The procedure of Bai and Perron (1998) allows for the presence of disturbance heteroskedasticity and/or autocorrelation using the approach of Andrews (1991). Our implementation requires only HC inference, which follows Bai and Perron (1998) in using the Andrews (1991) method.

we re-test breaks in the coefficients conditional on the variance breaks from step 4. That is, we apply the feasible GLS transformation[4] and, assuming homoskedasticity in the error term, the Bai and Perron (1998) procedure is performed again on the new transformed data in order to obtain volatility adjusted coefficients break dates for the model specified in step 2. If no volatility breaks are found from step 4, coefficient tests are applied to the original data with a homoskedastic variance assumption, and the iteration ends.

The iterative testing procedure outlined above differs from the methodology by Bataa et al. (2013a) in several respects. Firstly, Bataa et al. (2013a) test for breaks in seasonal components as part of the iterative procedure whereas we apply seasonal adjustment procedure to the data once prior to beginning of our iterative procedure. Secondly, outlier detection procedure in step 1* takes account of the latest identified coefficient and variance breaks while variance breaks are ignored when detecting outliers in Bataa et al. (2013a). Thirdly, in step 2 we re-specify the model employed at each iteration, reflecting the effects of detecting and removing outliers. This is not a concern in Bataa et al. (2013a).

Fourthly and most importantly, the preliminary coefficient break test in step 3 (where mean and dynamics are jointly tested) employs HC inference to account for possible heteroskedasticity in the variance. For their initialization, HAC inference is employed when testing for mean breaks to account for un-modeled dynamics and variance, and later they employ HC inference when testing for breaks in dynamics on the demeaned data. However, as mentioned previously, this procedure can be substantially oversized, therefore and consequently we jointly test for mean and dynamic breaks. Finally, the iterative procedure

[4]This methodology is based on the findings by Pitarakis (2004) who revealed substantial improvement of this transformation in small samples by comparing bootstrap based test on both transformed and untransformed data.

by Bataa et al. (2013a) incorporates 'inner loop' that iterates between tests for breaks in the dynamics and the residual variance. However, as shown by their Monte Carlo simulation, variance breaks are detected well without iteration. Our variance break testing procedure in step 4 simplifies the iterations in respect to identification of variance breaks. In each iteration, possible breaks in the residual variance are tested once conditional on coefficient breaks detected from step 3.

A single iteration is composed of steps 1 to 5. The iterations proceed to convergence, with a maximum number of iterations set to 10. Convergence may be achieved in two different ways: firstly, the same set of break dates may be obtained from consecutive iterations; alternately, the iteration can cycle between two or three sets of break dates. In the later case, we choose the set which achieves the smallest SIC criterion among these local optima. When calculating SIC for this purpose, we use a fixed number of observations, T. The version of SIC is that proposed by Yao (1988) for structural break inference, which is applied to the GLS transformed data and calculated for m breaks as

$$SIC(m) = \ln \hat{\sigma}^2(m) + p^* \ln(T)/T, \tag{2}$$

where $\hat{\sigma}^2(m) = T^{-1} S_T(\hat{T}_1, \ldots, \hat{T}_m)$, in which $S_T(\hat{T}_1, \ldots, \hat{T}_m)$ is a sum of squared residuals over m breaks, and $p^* = (m+1)q + m$ in which q equals the number of coefficients (including the intercept) in (1). Thus, the penalty effectively treats each break date as a parameter to be estimated.

A single iteration accounts for the main issues that we address in this paper - namely, the integrity of estimated mean, persistence and variance breaks. However, on the one hand, those break dates from steps 4 and 5 can have a considerable impact on the outlier detection procedure of step 1. For example, an outlier detected using the full sample may not be an outlier for a certain high volatile regime but appear as an outlier compared to a smooth part of the sample.

Similarly, an outlier appearing in the relatively stable regime may be too small to be detected using the full sample compared to a volatile part of the sample. On other hand, a different set of outliers can be found from one iteration to another depending on the variance and coefficient breaks identified in the previous iteration, and newly identified outliers also can have an impact on the identification of coefficients and variance breaks in the following steps. Hence, the need for iteration.

2.2 Estimating the number of breaks

The heart of the iteration described in the above subsection is the multiple structural break testing procedure by Bai and Perron (1998)[5]. Say the model of (1) has a maximum of m coefficient breaks and hence $m+1$ regimes, $j = 1, \ldots, m+1$. The estimates of the parameters and the optimal break dates are computed using the dynamic programming algorithm of Bai and Perron (1998, 2003a), which searches for the minimum total residual sum of squares over all $m + 1$ regimes. This yields m sets of possible break dates: that is, $1, 2, \ldots, m$ possible estimated break dates.

After m sets of possible estimated break dates are obtained, we employ two different tests: WDmax and sequential $Sup\ F(l + 1|l)$ to choose among those sets. First, we use WDmax[6] as an indication of the presence of at least one break. WDmax tests the null hypothesis of no breaks against the composite alternative of $1, \ldots, m$ breaks and failure to reject the null hypothesis then zero breaks are estimated to occur. As recommended by Bai and Perron (1998, 2003a), when

[5]We adapt the MATLAB code for testing multiple structural breaks which is originally developed by Pierre Perron in the GAUSS program and translated later to MATLAB program by Yohei Yamamoto (2012).

[6]The WDmax statistic is used in preference to UDmax because it embodies a set of weights that ensure the marginal p-values are equal for the null of no breaks against each specific number of breaks $1, 2, \ldots, m$ (Bai and Perron, 1998).

the null hypothesis is rejected, their sequential $SupF(l+1|l)$ test is employed to estimate the appropriate number of breaks. That is, the null hypotheses of $l = 1, 2, 3, \ldots$ breaks (subject to a maximum of m breaks) are examined sequentially against the alternative of $l+1$ breaks, with the first non-rejection yielding l breaks. In particular, this test is applied first for 2 versus 1 break (not 1 versus 0) due to the difficulty of rejecting the null hypothesis of zero versus a single break in the sequential test, especially in a case that the value of the coefficients returns to its original value after the second break when two breaks are present (Bai and Perron, 2003a, 2006). Sequential $Sup\ F(l+1|l)$ tests are conducted due to their good performance under both presence and absence of serial correlation and heterogeneity compared to the use of information criterion (Bai and Perron, 2006).

All tests are computed at a nominal 5 percent level of significance, with the maximum number of breaks considered being $m = 5$. Testing employs the asymptotic distributions obtained by Hall and Sakkas (2013), which are shown by these authors to more accurate than the critical values provided by Bai and Perron (2003b) and have the additional advantage of allowing computation of asymptotic p -values. The so-called trimming parameter, which defines the minimum distance between two consecutive breaks as a function of the total sample size T is set at 0.15.

More specifically, the testing procedure we describe in this section relates to steps 3, 4 and 5 of the iteration above. We first test H_0 : $\mu_j = \mu_{j+1}$ and $\alpha_{i,j} = \alpha_{i,j+1}$ for $j = 1, \ldots, m$ against the alternative of $H_A : \mu_j \neq \mu_{j+1}$ or $\alpha_{i,j} \neq \alpha_{i,j+1}$ for at least some $m \leq M$ (M is an upper bound), using

$$WD\ \max F_T(M, q) = \max_{1 \leq m \leq M} a_m [\sup_{(\lambda_1, \ldots, \lambda_m) \in \Lambda_\epsilon} F_T(\lambda_1, \ldots, \lambda_m; q)] \quad (3)$$

where λ_j for $j = 1, \ldots, m$ are possible break dates as fractions of the sample size, and Λ_ϵ denotes the set of all possible sample partitions given ε which is the smallest fraction of the sample that must be included in each segment, satisfying $0 < \varepsilon < 1$. For $m > 1$, $a_m = c(q, \alpha, 1)/c(q, \alpha, m)$ in which $c(q, \alpha, m)$ is the asymptotic critical value of the test $\sup\limits_{(\lambda_1,\ldots,\lambda_m)\in\Lambda_\epsilon} F_T(\lambda_1, \ldots, \lambda_m; q)$ at a significance level α, where $\sup F_T$ is given as

$$\sup F_T(\lambda_1, \ldots, \lambda_m; q) = \sup[\frac{1}{T}(\frac{T-(m+1)q}{mq})\hat{\delta}' R'(R\hat{V}(\hat{\delta})R')^{-1}R\hat{\delta}] \tag{4}$$

where q is the number of regressors that are allowed to change and $\hat{\delta} = (\hat{\mu}_j, \hat{\alpha}_{1j}, \ldots, \hat{\alpha}_{nj})$. We allow the covariance matrix of $\hat{\delta}$ to evolve as $\hat{V}(\hat{\delta}_j) = \hat{\sigma_j}^2[(\Delta\widehat{T}_j)^{-1}\sum_{t=\widehat{T}_{j-1}+1}^{\widehat{T}_j} Z_t Z_t']^{-1}$ where $\widehat{\sigma}_j^2 = (\Delta\widehat{T}_j)^{-1}\sum_{t=\widehat{T}_{j-1}+1}^{\widehat{T}_j} \hat{\upsilon}_t^2$ for $j = 1, ..., m+1$, under the HC inference and $Z_t = (1, \pi_{t-i}^{D'})$ is the vector of regressors. The HC case here, however, only allows for variance breaks that coincide with coefficient breaks. R is a matrix of restrictions such that $(R\delta)' = \left(\delta_1' - \delta_2', ..., \delta_m' - \delta_{m+1}'\right)$.

Once the WDmax test rejects the null of no breaks, we employ *Sup* $F(l+1|l)$ to define the number of optimal breaks using

$$\begin{aligned} F_T(l+1|l) = \{&SSR_T(\widehat{T}_1, \ldots, \widehat{T}_l) \\ &- \min_{1\leq j\leq l+1} \inf_{\tau\in\Lambda_{j,\varepsilon}} SSR_T(\widehat{T}_1, \ldots, \widehat{T}_{j-1}, \tau, \widehat{T}_j, \ldots, \widehat{T}_l)\}/\widehat{\sigma_j}^2 \end{aligned} \tag{5}$$

where $\Lambda_{j,\varepsilon} = \{\tau; \widehat{T}_{j-1} + (\widehat{T}_j - \widehat{T}_{j-1})\varepsilon \leq \tau \leq \widehat{T}_j - (\widehat{T}_j - \widehat{T}_{j-1})\varepsilon\}$.

Here one additional break is inserted, conditional on the break dates already uncovered and assessed whether additional break reduces the overall sum of squared residuals. For example, the null hypothesis of l breaks is rejected against the alternative of $l+1$ if its overall sum of squared residuals is sufficiently larger than the sum of squared residuals from the model with $l+1$, and it continues sequentially until the testing procedure fails to reject the null hypothesis.

At step 3 of the iteration, we obtain the estimated coefficient break dates under equations (3) to (5) and denote these as $\widehat{T}_1^C, \ldots, \widehat{T}_m^C$. After obtaining the estimates of $\hat{\delta} = (\hat{\mu}_j, \hat{\alpha}_{1j,\ldots,}\hat{\alpha}_{nj})$ and the corresponding coefficient break dates $\widehat{T}_1^C, \ldots, \widehat{T}_m^C$, we estimate the variance of residuals by first concatenating the squared residuals in each regime

$$\hat{\upsilon}_t^2 = (\pi_t^D - \widehat{\mu}_j - \sum_{i=1}^{n} \widehat{\alpha}_{i,j}\pi_{t-i}^D)^2 \tag{6}$$

where $j = 1, \ldots, m+1$ and $t = \hat{T}_{j-1}^C + 1, \ldots, \hat{T}_j^C, E(\upsilon_t) = 0$ are assumed.

Then at step 4 of the iteration, we run the tests described in equations (3) to (5) again on the variance of residuals through the regression

$$\hat{\upsilon}_t^2 = \gamma_j + u_t \tag{7}$$

where γ_j is a constant whose value is allowed to change over time.

At step 5, if any variance breaks[7], denoted as $\hat{T}_1^V, ..., \hat{T}_m^V$, are found in the equation (7), we calculate the standard errors in each regime as $\hat{\sigma}_j = \sqrt{(\Delta\widehat{T}_j^{\,V})^{-1} \sum_{t=\widehat{T}_{j-1}^V+1}^{\widehat{T}_j^V} \hat{\upsilon}_t^2}$. Then, the standard error in each regime is used to standardize the data that leads GLS transformation, $\bar{\pi}_t^D = \frac{\pi_t^D}{\hat{\sigma}_j}$ $\bar{\pi}_{t-i}^D = \frac{\pi_{t-i}^D}{\hat{\sigma}_j}$ $\bar{\mu}_j = \frac{\mu}{\hat{\sigma}_j}$ where $t = \hat{T}_{j-1}^V + 1, \ldots, \hat{T}_j^V$. Then coefficient break testing is applied to the model using GLS transformed data, but under the homoskedastic assumption so that the covariance matrix of $\hat{\delta}$ is obtained as $\hat{V}(\hat{\delta}_j) = \hat{\sigma}^2 \left[(\Delta\widehat{T}_j^{\,C})^{-1} \sum_{t=\widehat{T}_{j-1}^C+1}^{\widehat{T}_j^C} Z_t Z_t'\right]^{-1}$ with $\widehat{\sigma}^2 = (T)^{-1} \sum_{t=1}^{T} \hat{\upsilon}_t^2$.

[7]Note that although m is used to denote the number of both coefficient and variance breaks, in practice we allow different numbers of breaks to apply for these components.

2.3 Testing in the bivariate model

So far, we have focused on univariate inflation models to test for structural breaks using our iterative methodology. This subsection introduces the bivariate model of principal interest, which examines changes in the degree of interdependence of domestic and foreign inflation. For this purpose, a parsimonious representation of domestic inflation for country s in month t ($\pi^D_{t,s}$) is given by

$$\pi^D_{t,s} = \mu_j + \sum_{i=1}^{n} \alpha_{ij}\pi^D_{t-i,s} + \beta_{0j}\pi^F_{t,s} + \sum_{i=1}^{n} \beta_{ij}\pi^F_{t-i,s} + \varepsilon_t \qquad (8)$$

where $\pi^F_{t,s}$ is foreign inflation in relation to country s at time t, and β_{0j} captures the contemporaneous co-movement between domestic and foreign inflation in coefficient regime j. Inflation in country s also depends on its own lags and the lags of foreign inflation, where the effects are captured through $(\alpha_{1j}, \ldots, \alpha_{nj})$ and $(\beta_{1j}, \ldots, \beta_{nj})$ coefficients respectively. Foreign inflation is treated as weakly exogenous for domestic inflation. Inflation persistence for country s in this model is measured by $\hat{\rho}^d_j = \sum_{i=1}^{n} \hat{\alpha}_{ij}$.

The motivation for the form of (8) is the Global-VAR (GVAR) analysis which examines international links using country-specific foreign variables. For instance, Pesaran et al. (2004) model each domestic macroeconomic variable considered in terms of its own lags, contemporaneous foreign variables and their lags. The US is a special case in their studies, with foreign inflation and output excluded from the US model as they assume that it violates weak exogeneity. Our bivariate model of inflation in (8) is similar, but in a single equation context in order to focus on international linkages of inflation. This allows us to test for time variations without losing too much power. Additionally, we include contemporaneous foreign inflation in the US model. This follows the arguments of Dees et al. (2007), that, in a foreign context and as the number of countries increases, this variable can be treated as weakly exogenous also for the US.

We anticipate breaks in the foreign coefficients $(\beta_{0j}, \beta_{1j}, \ldots, \beta_{nj})$, if there are changes in the way in which domestic inflation relates to foreign inflation. Additionally, the locations of breaks in the $(\mu_j, \alpha_{1j}, \ldots, \alpha_{nj})$ coefficients may differ from those found in the univariate models of equation (1), due to the inclusion of foreign variables. Although we do not employ tests to disentangle explicitly what elements of $\delta_j = (\mu_j, \alpha_{1j}, \ldots, \alpha_{nj}, \beta_{0j}, \beta_{1j}, \ldots, \beta_{nj})$ change at break dates, coefficient estimates in each regime are informative with regard to this.

Inference as to the presence and dates of the breaks in (8), including breaks in the disturbance variance, is achieved by employing the iterative procedure outlined in subsection 2.1 and the multiple break testing methodology in subsection 2.2. Although the general procedure is the same as in the univariate analysis, some additional remarks should be made. In step 1 of the iteration (step 1* for subsequent iterations), the outlier detection and removal procedure runs only on domestic inflation because aberrant observations in the explanatory variables should not affect the size of the test. Furthermore, we note that the presence of a break in the explanatory variable does not affect the size of the test[8]

In step 2, we choose bivariate models in a slightly different manner from the univariate models. Employing the same model selection method is computationally excessive, since the best model would be selected out of 2^{25} possible models, provided that the maximum lags allowed for domestic and foreign variables are 12 each plus a contemporaneous foreign variable. Therefore, we employ a general to specific methodology to remove irrelevant lags from the general model, but still decide the best model based on SIC. Precisely, we start by evalu-

[8] Allowing a single break in the process generating the explanatory variable occurring in the middle or towards the end of the sample, the test is well-sized at a 5% significance level, based on 5000 replications.

ating the model with 25 lags (12 lags for each of domestic and foreign inflation plus a contemporaneous foreign inflation), then the least significant lag using t-tests is eliminated and corresponding information criterion (SIC) is calculated. Continuing by sequentially dropping the least significant lag one at a time, until only the intercept remains, we choose the model which achieves the smallest SIC criterion across all 25 models.

However, the selected model is the optimum within a single path. There could be multiple paths that yield different optima depending on the starting point of elimination. Therefore, we check the sensitivity of the model selection to the starting point using the idea of the multipath search algorithm, proposed by Krolzig and Hendry (2001). To be specific, we proceed through 5 paths by initially eliminating the z^{th} (where $z = 1, \ldots, 5$) least significant variable. Once the first variable is dropped, the least significant variable is dropped at all subsequent stages. At the end of the search, we have 5 sets of SIC values from which the final model is selected based on the smallest SIC criterion[9] achieved among all values.

Moreover, in the sensitivity analysis (which we will discuss in detail in section 5), an additional explanatory variables is included in the bivariate model, with a contemporaneous and 12 lagged values added. The additional variables are oil price inflation and the change in trade weighted real effective exchange rates. The first is employed because a sudden increase in oil price can cause an exogeneous inflationary shock to domestic inflation, and omitting this variable may result upward bias in the estimated coefficients. The latter is included as it may be important in explaining domestic inflation, especially for open economies, through its influence on import and export prices.

[9] We also compare our information criterion based models with a conventional testing down method, using a significance level of 1%. In the latter approach, all remaining coefficients are significant at 1% but this does not necessarily achieve the smallest information criterion. It yielded very similar lags to those selected by SIC, except for the inclusion of an additional lag in a few cases.

The approach, including the way SIC is used for model selection, is unchanged from that employed for the bivariate models.

2.4 Measuring foreign inflation

We construct foreign inflation for country s (where $s = 1, \ldots, N$) based on a weighted average of inflation series over the other $N-1$ countries in the data set. Weights are computed based on bilateral trade statistics as,

$$w_{s,t}^{(i)} = \frac{(M_{s,t}^{(i)} + X_{s,t}^{(i)})}{\sum_{i=1,i\neq s}^{N}(M_{s,t}^{(i)} + X_{s,t}^{(i)})} \text{ and } \pi_{s,t}^{F} = \sum_{i=1,i\neq s}^{N} w_{s,t}^{(i)}\pi_{i,t} \tag{9}$$

where $\sum_{i=1,i\neq s}^{N} w_{s,t}^{(i)} = 1$ for $i = 1, \ldots, 19$ and $i \neq s$. The trade weight for country s with respect to country $i, w_{s,t}^{(i)}$, is given by the share of total trade between country s and i, in the total trade of country s with all its trading partners. Precisely, the total trade of country s with country i is measured by the sum of total imports from i ($M_s^{(i)}$) and exports to i ($X_s^{(i)}$). The weights are time varying and changes from month to month are relatively small, although this is not generally the case over the entire sample period. After computing trade weights, country specific foreign inflation is constructed as in (9) for each of the 19 countries in our sample.

3 Data

The data set we use in our analysis comprises of monthly aggregate series of Consumer Price Index (CPI) inflation for 19 OECD countries over the period between January 1970 and September 2010. These include ten countries that are members of the Euro Area (Austria, Belgium, Finland, France, Germany, Greece, Italy, Netherlands, Portugal, Spain), five other European countries (Denmark, Norway, Sweden, Switzerland, UK) and four other countries (Canada, Japan, Korea, US). All inflation series are calculated by differencing logged monthly indexes and multiplying by 100 where monthly CPI values are obtained from the OECD Main Economic Indicator database. Since we are using monthly series, seasonal oscillation is high and taken care of using the X12-ARIMA filter.

We also use monthly values of trade, which is defined by the sum of total exports and imports, by partner countries to construct trade weights using equation (9). According to the OECD Main Economic Indicator statistical website, all series are expressed in US dollars using (where appropriate) the exchange rates which adjust the rates before and after the start of the European Monetary Union (EMU). This adjustment facilitates a comparison within and across countries. The range of trade data is the same as CPI inflation although there are some missing data for Belgium, Korea and Portugal. Korea starts registering bilateral trade data from January 1988 and Belgium from January 1993. Portugal has missing trade data with respect to Italy between January 1971 and December 1973. Due to those missing observations, the trade weights corresponding to those periods are filled by the first available weight after the missing observations. This does not unduly distort the data since monthly weights are generally smooth over the 40 years of our sample.

Table 1 shows bilateral trade weights averaged over 40 years. In general, Germany is the biggest trade partner for most European countries, while the US is the main trade partner for non-European countries such as Japan, Korea and Canada. However, the UK does not have a dominant trade partner, although shares with respect to Germany, US and France are relatively large compared to others. Those weights are informative to construct a country specific foreign inflation, by taking account of contributions of trading partners' inflation. We should note, however, that weights based on bilateral trade statistics may be limited as they do not reflect trade effects of a third-country such as the big emerging economies of China and India. But, the limitation of data for those countries precludes their use.

For the sensitivity analysis in section 5, the world average crude oil price index, over the period between January 1970 and September 2010, is used to calculate oil price inflation which is added as an additional variable in equation (8). This is available from the OECD Main Economic Indicator database. Another variable added in equation (8), although not at the same time with oil price inflation, is monthly averaged trade weighted real effective exchange rate indexes for individual country. This is obtained from the Bank of International Settlement database. Changes in these variables are computed by differencing logged monthly indexes and multiplying by 100, consistent with the construction of CPI inflation.

4 Results

This section presents the results. Section 4.1 provides a summary of results for the univariate inflation models. Section 4.2 presents the results for bivariate inflation models and discusses inferences with regard to the spillovers from foreign inflation to domestic inflation. All tests are conducted at the 5 percent significance level allowing a maximum of 5 breaks with value of trimming $\varepsilon = 0.15$, such that a minimum fraction of the sample in each regime equals to approximately 73 months. Asymptotic p-values are approximated using the method of Hall and Sakkas (2013).

4.1 Univariate inflation models

Table 2 represents the selected autoregressive lags of the univariate and bivariate inflation models; the latter are discussed in section 4.2. In the univariate models, we always find short lags to be present (say, 1, 2 and/or 3) when the maximum lag allowed is 17. This is not surprising as the recent past is more relevant. Also, longer lags (say 11, 12 and/or 13) are often found and this could indicate that some seasonal effects may still be present.

Table 3 reports the break dates uncovered in the univariate coefficients and residual variances. This table also indicates the number of iterations required for convergence of the testing procedure of subsection 2.1. All countries except Finland converge to a unique set of break dates, whereas for Finland the iterative procedure cycles between two local optima, in which the one with the smaller SIC is selected. We note that the iteration is necessary as convergence usually requires more than one iteration. However, our application requires no more than four iterations (except for Finland), highlighting the efficiency of our iterative methodology.

We also provide a figure for every country (figure 1.1-1.19, in alphabetical order) in the web appendix to preserve space, each comprising four graphs. The first two graphs in each figure correspond to the univariate specification and compare the difference between before and after iteration. Specifically, the first graph presents the break dates as well as some statistics relating to the corresponding regimes from applying the testing procedure of subsection 2.1 once, while the second graph reports the results after iterating the testing procedure multiple times until the convergence. For the majority of cases, the results in the first graphs can be seen as intermediate results to the second graphs as convergence usually requires more than one iteration, and thus the results in the second graphs are discussed in this subsection. However, in many cases identical results appear from employing the testing procedure once and iterating multiple times, indicating the effectiveness of the proposed testing procedure. Similarly, the third graph in each figure relates to the bivariate specification after iteration and these are discussed in the next subsection. The last graph in each figure plots country specific foreign inflation for each corresponding country. This series is also plotted in the third graph in order to compare dynamics between domestic and country specific foreign inflation.

To illustrate, refer to figure 1.18b for the univariate specification of UK inflation, for example. The vertical lines indicate the locations of the coefficient break dates with the estimated dates (June 1982 and December 1991) in the boxes next to these lines. Text arrows point to the locations of variance breaks and the corresponding changes in the variance of the consecutive regimes. The variance break occurring around April 1982 leads to a reduction of the variance from 0.13 to 0.03. Furthermore, the estimates of persistence and the unconditional mean in each regime, denoted by P and UcM respectively, are shown in the boxes. These estimates are indicative with regard to their changes over time. Outliers detected at the convergence of the iterations are indicated by black dots if any outliers are detected, with three outliers found in UK inflation over 40 years.

Overall, we find a total of 26 coefficient breaks across all 19 countries, with Austria and Switzerland having no breaks. This compares with the total of 23 mean and dynamics breaks obtained by Bataa et al. (2013a) for only 8 countries, despite the similar iterative approaches. For example, they uncover 4 mean breaks for France, whereas we find 2 significant breaks over a longer sample period[10]. This may point to their testing procedure being oversized if mean and dynamic breaks are considered separately.

Nevertheless, the timing of breaks presented in Table 3 is broadly consistent with the existing literature. We find clusters of coefficients breaks around the first half of the 1980s (although breaks for France, Spain and Norway are estimated to occur shortly after this) and early 1990s. The first cluster of breaks is widely considered to be a conse-

[10]Bataa et al. (2013a) use data between March 1973 and December 2007.

quence of disinflation policies in a number of countries including the US and UK (Altissimo et al., 2006; Benati and Kapetanios, 2002, etc), and the currency peg in France, Italy and Netherlands which was designed to mimic the low inflationary experience in Germany (Altissimo et al., 2006). Consistent with this view, the unconditional mean declines to less than half of its pre-break value for most countries. The cluster in the early 1990s includes many European countries and may be related to the implementation of the Maastricht Treaty in 1992, in which inflation rates in the countries joining the Euro Area were required to converge. Additionally, break dates for the UK and Canada seem to relate closely with their introduction of inflation targeting policies in October 1992 and February 1991, respectively. In relation to these later breaks, further declines in the unconditional mean are observed with a smaller magnitude than the declines in the 1980s. The largest decline is in the mean of Japan after December 1991, pushing it to a negative value. These changes in unconditional mean can be seen in their respective country's figure.

A figure for each country (figure 1.1-1.19, in alphabetical order) also reports the estimates of persistence in each coefficient break regime. In common with the existing literature, the results show that estimated inflation persistence is generally smaller after the coefficient breaks, especially in the latter part of the sample. In most cases (12 out of 19 countries) estimated persistence is high, between 0.60-0.90 before the first break, but it falls substantially in later regimes and almost disappears in the last regime. This contrasts with the finding by Cecchetti and Debelle (2006); O'Reilly and Whelan (2005) and others, who detect weak evidence for persistence change over time. However, in line with these studies, we find that relatively stable persistence applies in Norway, Germany and Netherlands. In the cases of Portugal and Spain, persistence declines after the first break, but increases back to previous high persistence levels after the early 1990s (see figures 1.14b and 1.15b).

Visual inspection indicates that every country experiences a highly volatile inflation period that lasts until either the late 1970s or mid-1980s depending on the country, with volatility decreasing afterwards. For Canada, Norway and the US we find volatility increases again around the early 2000s (see figures 1.3b, 1.13b and 1.19b). Consistent with this observed pattern, our results imply an equal number of variance and coefficient breaks, stressing the importance of variance break testing, which is largely absent from the existing literature. More importantly, although the clustering pattern of mean breaks is widely documented in the literature, we find also a clustering of variance breaks. For example, we find declines in variances around 1977 for eight countries, which may reflect the stabilization of inflation after the large oil price shocks of 1973-1974. An even larger number of breaks (14 in total) occur in the first half of the 1980s, reflecting "the great moderation". A few breaks also occur around 1992, which may be an effect of stabilization due to inflation targeting policies; for example, in Greece and Portugal.

Finally, we emphasize the importance of the outlier detection. Searching for outlier values in the coefficient break regimes using volatility standardized data yields more plausible outliers compared to those detected using the full sample. For example, an outlier in April 1991 in the UK does not appear as an outlier in the full sample when compared to the high inflation experienced during periods of the oil price shocks. However, our procedure distinguishes regimes with high and low levels of inflation in which this visually evident outlier is identified.

More importantly, the outlier detection procedure appears to have a considerable impact on inferences concerning coefficient and variance breaks. Each iteration hinges on the outlier detection procedure such that the only thing that changes from one iteration to another is a different set of outliers depending on the variance and coefficient breaks identified in the previous iteration. The difference between a single iteration (graph a in each figure) and multiple iterations (graph b in each figure) with an outlier detection procedure is sometimes striking. For example, see figures 1.5, 1.10 and 1.16 where outliers contaminate both variance and coefficient breaks, see figures 1.12 and 1.18 in which outliers complicate the detection of mean breaks and see figures 1.15 and 1.19 where variance breaks change after outlier iteration. Since the results taking account of outliers iteratively always visually appear more reliable than those obtained using the full sample information with no account taken of breaks, we conclude that our conditional break point testing method with outlier iteration adds value to the existing literature.

4.2 Models with foreign inflation

As previously mentioned, Table 2 reports the models for the relationship between domestic and foreign inflation selected by our SIC-based approach. Furthermore, we note that employing multipath searches with different starting points does not change the models given by a single search. Generally, the bivariate models are more parsimonious than the univariate ones, with the number of domestic AR lags declining when the foreign variable is added; indeed, Austria and Germany now have no AR lags. Furthermore, contemporaneous foreign inflation plays a key role, with lags of this variable absent for most countries. Portugal is the only case where contemporaneous π_t^F is not selected. However, it is included in the estimated models for this case for comparability with other countries.

We also turn to figures 1.1-1.19, where the third graph of each presents the results of the bivariate models. In each case, country-specific foreign inflation is represented by the red line. Based on these numerical and graphical illustrations, the results of our analysis can be summarized as follows.

Firstly and most importantly, we find a positive and increasing contemporaneous relationship between domestic and country-specific foreign inflation. It is particularly notable after 1990 for most countries (but could be after 1980 or 2000 for a few countries) and the corresponding estimated coefficient (β_{0j} in equation (8)), on average across countries, more than doubles compared to the pre-break regime. The third graph of each figure presents this coefficient. It is also visually evident in the graphs that the differences between domestic and foreign inflation gets smaller in the later period of the sample.

There are exceptions to this, however, in a small number of cases. For example, UK, Korea and Netherlands (figures 1.18c, 1.11c and 1.12c, respectively), show almost constant contemporaneous interactions over time, while their marked changes in the domestic indicators are evident. This suggests that the observed breaks are due to internal factors such as monetary policy changes. Another exception is Japan (figure 1.10c), where the contemporaneous effect is high during the oil price shocks in the first half of the 1970s, and declines afterwards. Regardless of these exceptions, a notable increase in the contemporaneous relationship may be informative with regard to co-movements of inflation. This is in line with Bataa et al. (2013b) who note increased contemporaneous international inflation linkages for the major G-7 economies they examine.

Secondly, inclusion of foreign inflation in the bivariate models can substantially change the identified break dates, pointing to the relevance of foreign inflation in explaining changes in domestic inflation. Specifically, there are three different patterns of break point changes compared to the univariate models. First, the number of coefficient breaks increases for a small number of countries, including Austria, Germany, Switzerland and the US. It is clear for Austria (figure 1.1c) and Switzerland (figure 1.17c) that the new breaks reflect changes in the relationship between domestic and foreign inflation, as the univariate models did not exhibit any breaks. For Germany, a coefficient break in 1981 is replaced by a variance break, and two more coefficients breaks are detected in 1976 and 1990 (see figure 1.7c). Following each break, an increase in the contemporaneous foreign inflation coefficient and a decrease in the unconditional mean are found. Additionally, the relatively high and constant persistence observed in the univariate specification seems to be knocked out by foreign inflation, as no lags are selected in the bivariate case. For the US, the break in 1990 is primarily domestic, leading to lower persistence and lower mean (see figure 1.19c). Although not detected in the univariate analysis, the 1977 break also appears as primarily domestic, whereas that in 2003 seems to be caused by an increased role of foreign inflation. In general, for Austria, Germany, Switzerland and US, the overall direction appears to be towards stronger linkages with foreign inflation.

Second, for some countries, the number of coefficient breaks decreases in the presence of foreign inflation. Interestingly, some coefficient breaks appear to be replaced by variance breaks, but not necessarily at the same date. For France and UK (figures 1.6c and 1.18c), for example, one coefficient break is replaced by a variance break while the remaining coefficient breaks hardly change their locations. Table 4 shows an increased number of variance breaks compared to the univariate models in Table 3, and corresponding large declines of variances, noted in the graphs. Indeed, newly obtained variance breaks seem to be located in more plausible places in a sense that they separate high and low volatility parts of the graph than the coefficient breaks of the univariate model. This may be indicative of the fact that the univariate models are essentially misspecified if foreign inflation is omitted. Possibly, an effect of the omitted variable may have been interpreted as a coefficient break which then disappears once relevant variable is included. However, this also could be related to the difficulty, discussed by Pitarakis (2004), of distinguishing between coefficient and variance breaks.

The third pattern covers countries where previously identified univariate coefficient breaks are altered although the number of breaks is unchanged. This may also indicate misspecification of the univariate models, as they omit effects of foreign environments. The largest variation in terms of location shifts of the coefficient breaks occurs in Japan by almost two decades (see figure 1.10). Variance breaks in univariate inflation, on the other hand, remain more or less the at same locations. However, for a few instances such as in Korea, Japan, Sweden and Spain (figures 1.11c, 1.10c, 1.16c and 1.15c, respectively), a new variance break appears in addition to the breaks identified in the univariate models. Finally, previously identified coefficient breaks are unchanged in the bivariate models of Norway and Sweden (figures 1.13c and 1.16c).

Despite the implied misspecification of univariate models, the general results of declining persistence and mean of domestic inflation remain in the bivariate models.

5 Sensitivity analysis

To assess the sensitivity of the results presented above, we extend the bivariate inflation models by including an additional variable which potentially has an impact on domestic inflation. The additional variables, oil price inflation and the change in trade weighted real effective exchange rates (EER)[11], are added to the bivariate models of inflation one at a time. These variables are measured in terms of percentage changes, as for CPI inflation. The first is employed because a sudden increase in oil price can cause an exogeneous inflationary shock

[11] We also employed the nominal effective exchange rates for the purpose of the robustness analysis. However, it is not picked up by the model selection procedure for any country, consequently yielding the same models as the bivariate inflation models.

to domestic inflation, and omitting this variable may result in upward bias in the estimated coefficients. Further, the effective exchange rate may be important in explaining domestic inflation, especially for open economies, through its influence on import and export prices.

The selected models including these variables are presented in Table 5 and Table 6 with the estimated coefficient and variance breaks using the selected models reported in Table 7 and Table 8, respectively. For convenience, the estimated coefficient and variance breaks using bivariate models (previously presented in Table 4) are repeated in Table 7 and Table 8, respectively. The results suggest that including either of these variables does not make a qualitative change for most countries.

In Table 7, previously identified coefficient breaks in bivariate models remain in a qualitatively similar location for most countries, when including oil price inflation in Table 5. The few exceptions are Belgium, Denmark, and US where some coefficient breaks are dropped, and Germany where the number of breaks increases. This indicates the potential misspecification of bivariate inflation models corresponding to these countries. Perhaps, in the absence of oil price inflation in bivariate models, its omitted effects to domestic inflation may have interpreted as an extra break in the estimation. While the number of coefficient breaks using bivariate models decreases when such variable is included in the model. For example, the US is known as one of the biggest oil importers, and two of three breaks (in 1970s and 1990s) are dropped when oil price inflation is included in the model. Despite the importance of oil price inflation for these countries, a decline in the number of breaks may also be due to a loss of power when testing for all coefficients.

Table 7 also compares coefficient breaks in bivariate models to the models with EER variable. EER appears to have less impact on big open economies and most of the Euro area. However, relatively small economies, Finland, Greece, Norway and Sweden, are sensitive to the inclusion of the EER. These countries yield an additional coefficient break which occurs prior or running up to the introduction of the European Monetary Union (EMU). The weakened role of EER after the EMU for these countries is evident in the estimates of the corresponding coefficients (see Table 10). Indeed, we do not expect large exchange rate fluctuations to play a role in explaining domestic inflation after the introduction of the EMU, especially for those belonging to EMU and who trade mostly with Euro area countries. Spain and Austria, on the other hand, drop coefficient breaks around early 2000. This may point misspecified bivariate models where the effects of the omitted exchange rate was captured previously as a break.

Furthermore, variance breaks obtained from the models with oil price inflation do not show any substantive differences from the breaks detected in the bivariate models. But, there is some variation from the model with EER for a small number of cases (see Table 8 for further details).

Table 9 and Table 10 provide estimated coefficients for models with oil price inflation and EER, respectively. Graphical illustrations of the results shown in these tables and comparison with bivariate models are given in figures 2.1-2.19 in the web appendix. Each figure consists of four graphs showing changes in the estimates of persistence, mean, contemporaneous foreign inflation, and the sum of the contemporaneous and (/or) lagged coefficients of third variables (EER and oil inflation). For Italy in figure 2.9, for instance, subplot (a) depicts changes in persistence that are estimated using the bivariate model (in black line), the model with oil price inflation (in red line) and the model with EER (in blue line). A similar interpretation applies to the contemporaneous foreign inflation coefficients and the subsample mean in subplots (b) and (c) respectively. Subplot (d) shows sum of estimated coefficients corresponding to the contemporaneous and lagged oil price inflation (in red line) and EER (in blue line). A missing line either in subplot (a) or (d) indicates the absence of the corresponding lags (and contemporaneous variable) in the model.

In general, despite the break point changes for a few cases above, conclusions drawn from the bivariate models largely carry over. Looking at the figures, estimated persistence and mean of inflation typically show substantial declining patterns regardless of the different models, represented by the lines in the graphs. Moreover, the increasing and positive contemporaneous relationship between domestic and foreign inflation remains robust. We should note, however, that there are some countries (Japan, Netherlands and the UK) where contemporaneous coefficients do not increase, but those are the same countries that show the constant contemporaneous effect in bivariate models of inflation. Finally, the figures also show that an impact of the lagged and (/or) contemporaneous third variables on domestic inflation is relatively small.

6 Concluding remarks

This paper adds to the existing literature on international inflation by comprehensively examining the structural stability in the relationship between domestic and country specific foreign inflation. For this aim, we propose and employ an iterative structural break testing methodology which is designed to deliver reliable inferences on structural breaks. In the iteration, we account for breaks in the conditional mean (which comprises intercept, autoregressive coefficients and coefficients on foreign inflation) and variance parameters by iterating between tests for conditional mean and variance breaks, while also taking care of outliers.

We document evidence of structural breaks in the linkage of domestic and country specific foreign inflation. Furthermore, taking into account the identified breaks, we find positive and increasing contemporaneous relationships between domestic and foreign inflation for most countries. This finding is compatible with the co-movement of inflation in different countries, documented widely in the literature (see Ciccarelli and Mojon, 2010; Neely and Rapach, 2011, etc). This also verifies the finding by Bataa et al. (2013b) who note increased contemporaneous correlations of inflation in a much more restricted number of G-7 countries. Moreover, the timing of breaks in mean and variances across countries exhibit notable clusters around the mid 1970s, early 1980s and early 1990s. The presence of such clusters already suggests the dependence of domestic inflation on foreign economic environments.

It appears to be widely accepted that changes in inflation have been mainly in the mean, with clusters of mean breaks documented in the univariate context. When applied to univariate inflation models, our procedure indicates that almost all countries in the data set experience at least one variance break, leading to substantial volatility declines. Furthermore, these breaks also show a clustering pattern. Overall the results from both univariate and bivariate inflation models suggest, declining unconditional mean and persistence of domestic inflation, consistent with the existing findings. Results on changes in inflation co-movement are robust to the inclusion of either oil price inflation or real effective exchange rates.

Finally, we emphasize that the use of the iterative structural break testing procedure was important to establish these findings. As shown using some illustrated cases in subsection 4.1, not employing this iterative procedure would lead to potentially substantial changes in the detected structural breaks compared to using non-iterated testing procedure.

Tables

Table 1: Trade weights by partner countries (monthly average over 40 years)

	Aus	Belg	Can	Den	Fin	Fra	Ger	Gre	Ita	Jap	Kor	Net	Nor	Por	Spa	Swe	Swi	Uk	US	SUM
Aus	0.000	0.025	0.008	0.012	0.009	0.052	0.488	0.006	0.111	0.025	0.005	0.035	0.007	0.006	0.018	0.024	0.072	0.047	0.050	1.000
Belg	0.011	0.000	0.005	0.009	0.006	0.209	0.246	0.005	0.059	0.024	0.004	0.177	0.009	0.009	0.030	0.018	0.016	0.100	0.064	1.000
Can	0.002	0.007	0.000	0.002	0.002	0.012	0.022	0.001	0.011	0.053	0.010	0.008	0.006	0.001	0.003	0.004	0.005	0.035	0.816	1.000
Den	0.013	0.032	0.008	0.000	0.033	0.058	0.241	0.006	0.047	0.032	0.006	0.063	0.066	0.007	0.018	0.157	0.021	0.125	0.070	1.000
Fin	0.015	0.032	0.010	0.045	0.000	0.059	0.191	0.006	0.043	0.040	0.009	0.056	0.047	0.008	0.022	0.181	0.022	0.132	0.083	1.000
Fra	0.011	0.120	0.010	0.010	0.007	0.000	0.239	0.008	0.136	0.029	0.007	0.069	0.012	0.013	0.073	0.019	0.042	0.099	0.096	1.000
Ger	0.061	0.091	0.011	0.025	0.013	0.155	0.000	0.010	0.107	0.038	0.010	0.126	0.019	0.010	0.037	0.032	0.059	0.090	0.106	1.000
Gre	0.017	0.043	0.007	0.014	0.011	0.099	0.250	0.000	0.174	0.063	0.019	0.072	0.006	0.004	0.034	0.021	0.021	0.077	0.069	1.000
Ita	0.033	0.053	0.013	0.012	0.007	0.193	0.261	0.018	0.000	0.023	0.007	0.062	0.007	0.010	0.051	0.017	0.055	0.078	0.101	1.000
Jap	0.005	0.017	0.057	0.008	0.005	0.032	0.081	0.006	0.023	0.000	0.109	0.029	0.008	0.003	0.011	0.011	0.020	0.053	0.524	1.000
Kor	0.004	0.010	0.033	0.005	0.005	0.025	0.066	0.004	0.024	0.339	0.000	0.021	0.005	0.001	0.010	0.008	0.011	0.036	0.392	1.000
Net	0.012	0.160	0.007	0.016	0.010	0.107	0.322	0.007	0.057	0.022	0.006	0.000	0.015	0.007	0.025	0.025	0.018	0.107	0.080	1.000
Nor	0.008	0.027	0.027	0.066	0.031	0.062	0.159	0.005	0.030	0.035	0.008	0.070	0.000	0.008	0.015	0.151	0.012	0.212	0.075	1.000
Por	0.011	0.040	0.009	0.015	0.010	0.130	0.177	0.003	0.069	0.025	0.003	0.054	0.015	0.000	0.179	0.030	0.028	0.126	0.080	1.000
Spa	0.010	0.039	0.010	0.010	0.008	0.208	0.184	0.007	0.107	0.033	0.007	0.053	0.007	0.049	0.000	0.019	0.024	0.101	0.124	1.000
Swe	0.016	0.046	0.011	0.092	0.073	0.062	0.186	0.005	0.041	0.030	0.007	0.063	0.103	0.008	0.020	0.000	0.022	0.123	0.092	1.000
Swi	0.050	0.036	0.009	0.013	0.008	0.126	0.317	0.005	0.112	0.041	0.006	0.045	0.006	0.007	0.025	0.022	0.000	0.076	0.098	1.000
Uk	0.011	0.068	0.033	0.026	0.018	0.117	0.169	0.006	0.062	0.043	0.009	0.102	0.035	0.012	0.038	0.042	0.040	0.000	0.170	1.000
US	0.005	0.027	0.354	0.006	0.004	0.046	0.089	0.003	0.037	0.207	0.048	0.035	0.007	0.003	0.016	0.014	0.020	0.077	0.000	1.000

Note: The shares for each country with respect to partner countries are given in the rows of the table.

Table 2: Autoregressive lags of univariate and bivariate models

Country	Univariate Models (maxlag=17)	Bivariate models (maxlag=12)	
	Domestic lags	Domestic lags	Foreign lags
Austria	[1;2;3;6;7;11]	NA	[0,4]
Belgium	[1;3;4;9;11;12]	[1;4]	[0]
Canada	[1;2;3;4;7;9;12;16]	[5;7;9]	[0,9]
Denmark	[1;3;6;8;11]	[1;3]	[0]
Finland	[2;5;6;7;9]	[2;9]	[0,4]
France	[1;3;6;8;12;17]	[1;3;10]	[0]
Germany	[2;6;7;8;9;11]	NA	[0]
Greece	[1;2;5;8;17]	[1;2;5;8]	[0]
Italy	[1;3;6;12;17]	[1;3;6]	[0,2]
Japan	[1;3;5;7;9;11;12;16]	[3;5;9;11]	[0]
Korea	[1;3;9;12;15]	[1]	[0,6]
Netherland	[1;4;6;7;8;17]	[4;6;8]	[0]
Norway	[1;2;3;7;8]	[1;3;7;8]	[0]
Portugal	[1;6;9;16]	[1;6;9]	[0,2]
Spain	[1;2;8;10;12;13;15]	[1;8;10]	[0]
Sweden	[2;3;7;8;9]	[7;8;9]	[0]
Switzerland	[1;2;4;6;10;17]	[1;6;9]	[0]
UK	[1;2;3;13]	[1;2;3]	[0]
US	[1;7;9;11;12]	[1]	[0]

Note: Autoregressive lags are obtained at convergence of the iterations.
For the domestic models, all combinations of lags are considered as discussed in subsection 3.1, while the bivariate models compared are based on a testing down approach as described in subsection 3.3. For both approaches, the final model is selected based on SIC.

Table 3: Breaks in univariate models

Country	Breaks in the set of coefficients				Breaks in the variances				
	1970s	1980s	1990s	2000s	1970s	1980s	1990s	2000s	NI
Austria	.	.	.	.	1977-Dec	.	.	.	1
Belgium	.	.	1994-Aug	2003-Dec	.	1985-Sep	.	.	2
Canada	.	1982-Jul	1990-Dec	.	1978-Nov	.	.	2000-Mar	2
Denmark	.	1982-Nov	1990-Jan	.	.	1980-Oct	1990-Dec	.	3
Finland	.	.	1991-Mar	.	1976-Nov	1983-Jul	.	.	[]
France	.	1986-Jan	1991-Dec	.	.	.	.	.	2
Germany	.	1981-Nov	.	.	.	.	.	.	2
Greece	.	.	1992-Nov	.	1977-Jul	.	1992-Sep	.	3
Italy	.	1982-Sep	1995-Jul	.	.	1981-Feb 1987-Jan	.	.	3
Japan	.	1980-Aug	1992-Jun	.	1977-May	.	1992-Jan	.	4
Korea	.	.	1998-Mar	.	.	1981-Mar	.	.	2
Netherland	.	1982-Feb	.	.	1978-Aug	.	.	.	3
Norway	.	1988-Apr	.	.	.	1982-Feb	.	2000-Dec	2
Portugal	.	1984-Aug	1992-Jun	.	1977-May	1985-Apr	1992-May	.	3
Spain	.	1986-Feb	1995-Mar	.	1977-Aug	1986-Aug	.	.	4
Sweden	.	.	1991-Feb	.	.	1985-Aug	.	.	3
Switzerland	.	.	.	.	.	1983-Feb	.	.	1
Uk	.	1982-Jun	1991-Dec	.	.	1982-Apr	.	.	4
US	.	.	1991-Feb	.	.	1982-Jul	.	2004-Oct	2
Total	0	11	14	1	8	13	4	3	

Note: Column NI represents the number of iterations required to converge to a single set of break dates. [] indicates the set of break dates is selected by a minimum SIC criterion.

Table 4: Breaks in bivariate models

Country	Breaks in the set of coefficients				Breaks in the variances				
	1970s	1980s	1990s	2000s	1970s	1980s	1990s	2000s	NI
Austria	1976-Sep	.	.	2000-Apr	1976-Sep				3
Belgium	.	1982-Apr	1995-Nov	.	.	1983-Nov	.	.	2
Canada	.	.	1990-Dec	.	1978-Nov	.	.	.	2
Denmark	.	1982-Nov	1994-Jun	.	.	1980-Oct	1991-Feb	.	3
Finland	.	.	1990-Mar	.	1976-Nov	1983-Jul	.	.	2
France	.	1985-Aug	.	.	.	1983-Jan	.	.	3
Germany	1976-Mar	.	1990-Sep	.	.	1982-Jul	.	.	[]
Greece	.	.	.	2000-Dec	1976-Oct	.	1993-Apr	.	2
Italy	.	1986-Jan	1996-May	.	.	1981-Feb 1987-Feb	.	.	2
Japan	1977-Jan	.	.	.	1977-Jan	1985-Nov	1993-Nov	.	2
Korea	.	1985-Sep	.	.	.	1982-Mar	.	2003-Apr	5
Netherland	.	1989-Apr	.	.	1978-Aug	.	.	.	3
Norway	.	1988-Apr	.	.	.	1980-Mar	.	.	3
Portugal	.	1985-Mar	1992-Jul	.	1978-May	1985-Mar	1992-May	.	2
Spain	.	1986-Jul	.	2004-May	1977-Nov	1986-Feb	1992-Nov	.	4
Sweden	.	.	1991-Feb	.	1977-Jul	.	1993-Jan	.	3
Switzerland	.	1984-Oct	.	.	.	1982-Jun	.	.	2
Uk	.	1980-May	.	.	.	.	1991-Aug	.	[]
US	1977-Nov	.	1990-Oct	2003-Feb	.	1983-May	.	2004-Sep	3
Total	4	11	9	4	9	14	7	2	

Note: Column NI represents the number of iterations required to converge to a single set of break dates. [] indicates the set of break dates is selected by a minimum SIC criterion.

Table 5: Sensitivity analysis: Selected models with oil price inflation

	Domestic lags	Foreign lags	Oil lags
Austria	N/A	[0,4]	[3]
Belgium	[1,4,9]	[0]	[0,5]
Canada	[5,7,9]	[0,9]	N/A
Denmark	[1,6,11]	[0]	[0,5]
Finland	[2,9,11]	[0,4]	[1]
France	[1,3,8,10]	[0]	[0]
Germany	[6]	[0]	[1]
Greece	[1,2,5,8]	[0,5]	N/A
Italy	[1,3,6]	[0,2]	[8]
Japan	[3,5,9,11]	[0]	[1]
Korea	[1]	[0,6]	[12]
Netherland	[4,6,8]	[0]	N/A
Norway	[1,6,8,10]	[0]	[12]
Portugal	[1,6,9]	[0*,2]	[1]
Spain	[1,8,10]	[0]	N/A
Sweden	[7,8,9]	[0]	[9]
Switzerland	[1,6,9]	[0]	[0,4]
Uk	[1,2,3]	[0]	N/A
US	[1,7]	[0]	[0,1]

Note: * indicates that the model selected by SIC does not include contemporaneous foreign variable. However, we test for breaks on the model including contemporaneous foreign inflation.

Table 6: Sensitivity analysis: Selected models with EER

	Domestic lags	Foreign lags	EER lags
Austria	[11]	[0]	[0]
Belgium	[1,4]	[0]	[0]
Canada	[5,7]	[0,9]	[0]
Denmark	[1,6]	[0]	[0]
Finland	[9]	[0,4]	[0]
France	[1,3,10]	[0]	N/A
Germany	N/A	[0]	[0,5]
Greece	[1,2,6,8]	[0]	[0]
Italy	[1,3,6]	[0,2]	[4]
Japan	[5,9,11]	[0,1]	[0]
Korea	[1]	[0,6]	N/A
Netherland	[4,6,8]	[0]	[0]
Norway	[1,2,6,8]	[0,11]	[0]
Portugal	[1,6,9]	[0*,2]	[0]
Spain	[1,2,8,9]	[0]	[5]
Sweden	[3,8,9]	[0]	[0]
Switzerland	[1,6,9]	[0]	N/A
Uk	[1,2,3]	[0]	N/A
US	[1]	[0]	N/A

Note: * indicates that the model selected by SIC does not include contemporaneous foreign variable. However, we test for breaks on the model including contemporaneous foreign inflation.

Table 7: Sensitivity analysis: Coefficient Breaks

Country	Bivariate models				Models with oil price inflation				Models with EER			
	1970s	1980s	1990s	2000s	1970s	1980s	1990s	2000s	1970s	1980s	1990s	2000s
Austria	1976-Sep	.	.	2000-Apr	1976-Sep	.	1999-Aug	.	.	.	.	.
Belgium	.	1982-Apr	1995-Nov	.	.	.	1995-Oct	.	.	1981-Nov	1995-Nov	.
Canada	.	.	1990-Dec	.	.	.	1990-Dec	.	.	1987-Feb	.	.
Denmark	.	1982-Nov	1994-Jun	.	.	1985-Apr	.	.	.	1989-Sep	1995-Sep	.
Finland	.	.	1990-Mar	.	.	.	1990-Feb	.	.	1983-Apr	1991-Jul	.
France	.	1985-Aug	.	.	.	1987-Jan	.	.	.	1985-Aug	.	.
Germany	1976-Mar	.	1990-Sep	.	.	1980-Nov 1987-Dec	.	2001-Feb	1976-Jul	.	1990-Sep	.
Greece	.	.	.	2000-Dec	.	.	.	2000-Dec	.	.	1994-Aug	2000-Dec
Italy	.	1986-Jan	1996-May	.	.	1986-Jan	1996-May	.	.	1986-Jan	1996-May	.
Japan	1977-Jan	.	.	.	1977-Jun	.	.	.	1977-Jan	.	.	.
Korea	.	1985-Sep	.	.	.	1981-Oct	.	.	.	1985-Sep	.	.
Netherland	.	1989-Apr	.	.	.	1989-Apr	.	.	.	1987-Jun	.	.
Norway	.	1988-Apr	.	.	.	1988-Apr	.	.	.	1981- May	.	.
Portugal	.	1985-Mar	1992-Jul	.	.	1985-Mar	1992-Jul	.	.	1984-Aug	1990-Oct	.
Spain	.	1986-Jul	.	2004-May	.	1986-Jul	.	2004-May	.	1986-Jul	.	.
Sweden	.	.	1991-Feb	.	.	.	1991-Feb	.	.	1983-Jan	1991-Feb	.
Switzerland	.	1984-Oct	.	.	.	1984-Oct	.	.	.	1984-Oct	.	.
Uk	.	1980-May	.	.	.	1980-May	.	.	.	1980-May	.	.
US	1977-Nov	.	1990-Oct	2003-Feb	.	.	.	2003-Feb	1977-Nov	.	1990-Oct	2003-Feb
Total	4	11	9	4	2	12	7	4	3	15	9	2

Table 8: Sensitivity analysis: Variance Breaks

Country	Bivariate models				Models with oil price inflation				Models with EER			
	1970s	1980s	1990s	2000s	1970s	1980s	1990s	2000s	1970s	1980s	1990s	2000s
Austria	1976-Sep				1976-Sep	.	.	.	1977-Jan	.	.	.
Belgium	.	1983-Nov	.	.	.	1984-May	.	.	.	1983-Jan	.	.
Canada	1978-Nov	.	.	.	1978-Nov	.	.	.	1978-Nov	.	.	.
Denmark	.	1980-Oct	1991-Feb	.	1977-Oct	1984-Apr	.	.	.	1983-Apr	1991-Mar	.
Finland	1976-Nov	1983-Jul	.	.	1977-Jan	1983-Jul	.	.	.	1983-Jul	.	.
France	.	1983-Jan	.	.	.	1983-May	.	.	.	1983-Jan	.	.
Germany	.	1982-Jul	.	.	1976-Sep	.	.	.	.	.	.	.
Greece	1976-Oct	.	1993-Apr	.	1976-Oct	.	1993-Jun	.	1976-Oct	1986-Mar	1994-Aug	
Italy		1981-Feb				1981-Feb				1981-Feb		
	.	1987-Feb	.	.	.	1987-Feb	.	.	.	1987-Feb	.	
Japan	1977-Jan	1985-Nov	1993-Nov	.	1977-Jan	1986-Mar	1993-Dec	.	1977-Jan	1985-Dec	1995-Nov	.
Korea	.	1982-Mar	.	2003-Apr	.	1981-Apr	.	2003-Apr	.	1982-Mar	.	2003-Apr
Netherland	1978-Aug	.	.	.	1978-Aug	.	.	.	1979-Feb	.	.	.
Norway	.	1980-Mar	.	.	.	1982-Aug	.	.	.	1982-Aug	.	2002-Dec
Portugal	1978-May	1985-Mar	1992-May	.	1978-May	1985-Feb	1992-May	.	1977-Mar	1985-Mar	1993-Sep	.
Spain	1977-Nov	1986-Feb	1992-Nov	.	1977-Nov	1986-Feb	1992-Nov	.	1977-Sep	1986-Feb	1992-Nov	.
Sweden	1977-Jul	.	1993-Jan	.	1977-Jul	.	1993-Jan	.	.	.	1993-Jan	.
Switzerland	.	1982-Jun	.	.	.	1983-Feb	.	.	.	1982-Jun	.	.
Uk	.	.	1991-Aug	.	.	.	1991-Aug	.	.	1982-Jul	.	.
US	.	1983-May	.	2004-Sep	.	1983-May	.	2004-Oct	.	1983-May	.	2004-Sep
Total	9	14	7	2	11	13	6	2	7	15	6	3

Table 9: Sensitivity analysis: Estimated coefficients in regimes

	Persistence	Mean	Foreign inflation (lags)	Foreign inflation (contemporaneous)	Oil price change (lags)	Oil price change (contemporaneous)
Austria	N/A	0.57; 0.27; 0.15	0.04; 0.29; 0.04	0.72; 0.35; 0.75	0.004; -0.0009; 0.004	N/A
Belgium	0.52; -0.02	0.43; 0.16;	N/A	0.51; 1.36	0.002; 0.003	0.003; 0.002
Canada	0.38; 0.008	0.55; 0.17	0.29; 0.08	0.23; 0.68	N/A	N/A
Denmark	0.25; 0.21	0.76; 0.21	N/A	0.55; 0.32	0.008; -0.0008	0.006; 0.007
Finland	0.36; 0.11	0.70; 0.17	0.07; 0.14	0.55; 0.70	0.004; 0.0007	N/A
France	0.68; -0.02	0.74; 0.16	N/A	0.34; 0.77	N/A	0.004; 0.002
Germany	0.28; -0.17; 0.07; 0.02	0.40; 0.23; 0.19; 0.13	N/A	0.08; 1; 0.65; 1.01	0.004; 0.003; 0.006; -0.006	N/A
Greece	0.75; -0.32	1.1; 0.27	0.04; 0.25	0.45; 0.93	N/A	N/A
Italy	0.59; 0.36; 0.22	1.06; 0.44; 0.18	0.63; 0.16; 0.16	0.05; 0.22; 0.41	0.007; 0.001; 0.0009	N/A
Japan	0.38; 0.23;	0.84; 0.12	N/A	0.43; 0.45	0.01; 0.0004	N/A
Korea	0.41; 0.19	1.24; 0.40	0.59; 0.17	0.42; 0.52	N/A	N/A
Netherland	0.56; 0.35	0.42; 0.18	N/A	0.46; 0.41	N/A	N/A
Norway	0.55; 0.30	0.68; 0.21	N/A	0.14; 0.51	0.006; -0.0008	N/A
Portugal	0.34; 0.01; 0.42	1.51; 0.99; 0.27	0.27; 0.52; 0.04	(-1.2; 0.22; 0.66)	0.02; 0.0007; -0.0008	N/A
Spain	0.41; 0.45; 0.19	1.09; 0.37; 0.21	N/A	0.46; 0.52; 1.2	N/A	N/A
Sweden	0.31; 0.14	0.67; 0.16	N/A	0.42; 0.82	0.008; -0.0009	N/A
Switzerland	0.60; 0.24	0.40; 0.14	N/A	0.20; 0.87	0.009; 0.001	0.0008; 0.002
UK	0.68; 0.33	1.03; 0.31	N/A	0.60, 0.58	N/A	N/A
US	0.42; 0.21	0.40; 0.19	N/A	0.37; 1.18	0.005; 0.003	0.005; 0.006

Table 10: Sensitivity analysis: Estimated coefficients in regimes

	Persistence	Mean	Foreign inflation (lags)	Foreign inflation (contemporaneous)	Change in EER (lags)	Change in EER (contemporaneous)
Austria	0.10	0.29	N/A	0.6	N/A	0.11
Belgium	0.51; 0.28; -0.01	0.58; 0.30; 0.16	N/A	0.53; 1.10; 1.39	N/A	0.07; 0.06; 0.04
Canada	0.25; 0.12	0.60; 0.20	0.31; 0.09	0.27; 0.69	N/A	0.08; 0.02
Denmark	0.21; -0.02; -0.01	0.66; 0.19; 0.17	N/A	0.79; 0.23; 0.77	N/A	0.09; 0.01; 0.05
Finland	0.28; -0.04; -0.04	0.85; 0.56; 0.14	0.24; -0.03; 0.18	0.49; 0.65; 0.76	N/A	0.16; 0.19; -0.0002
France	0.69; -0.04	0.77; 0.17	N/A	0.30; 0.81	N/A	N/A
Germany	N/A	0.47; 0.25; 0.16	N/A	0.18; 0.62; 0.92	0.07; -0.01; 0.01	0.04; 0.02; 0.03
Greece	0.47; 0.63; -0.13	1.26; 0.50; 0.27	N/A	0.32; 0.80; 0.88	N/A	0.09; -0.03; 0.007
Italy	0.61; 0.37; 0.18	1.06; 0.44; 0.18	0.62; 0.13; 0.16	0.08; 0.23; 0.42	0.03; 0.005; 0.01	N/A
Japan	0.24; 0.16	0.84; 0.13	0.36; 0.23	0.74; 0.35	N/A	0.12; 0.01;
Korea	0.43; 0.17;	1.05; 0.36	0.69; 0.21	0.60; 0.63	N/A	N/A
Netherland	0.57; 0.38	0.47; 0.17	N/A	0.51; 0.39	N/A	0.03; 0.04
Norway	0.22; 0.47; 0.23	0.66; 0.72; 0.21	0.45; -0.06; 0.05	0.20; 0.17; 0.39	N/A	N/A
Portugal	0.45; -0.13; 0.39	1.48; 1.11; 0.32	0.37; 0.48; 0.10	(-0.72; 1.06;0.65)	N/A	N/A
Spain	0.56; 0.30	1.08; 0.32	N/A	0.35; 0.88	0.04; 0.0007	N/A
Sweden	0.40;0.12; 0.22	0.75; 0.56; 0.16	N/A	0.40; 0.83; 0.85	N/A	0.03; 0.33; -0.0005
Switzerland	0.62; 0.20	0.40; 0.14	N/A	0.30; 0.94	N/A	N/A
UK	0.69; 0.39	1.03; 0.31	N/A	0.59; 0.59	N/A	N/A
US	0.02; 0.44; 0.10; 0.13	0.52; 0.49; 0.22; 0.19	N/A	0.66; 0.53; 0.39; 1.44	N/A	N/A

References

Altissimo, F., Bilke, L., Levin, A., Matha, T., and Mojon, B. (2006). Sectoral and Aggregate Inflation Dynamics in the Euro Area. *Journal of the European Economic Association*, 4(2/3):585–593.

Andrews, D. W. K. (1991). Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation. *Econometrica*, 59(3):817–858.

Bai, J. and Perron, P. (1998). Estimating and Testing Linear Models with Multiple Structural Changes. *Econometrica*, 66(1):47–78.

Bai, J. and Perron, P. (2003a). Computation and analysis of multiple structural change models. *Journal of Applied Econometrics*, 18(1):1–22.

Bai, J. and Perron, P. (2003b). Critical values for multiple structural change tests. *Econometrics Journal*, 6(1):72–78.

Bai, J. and Perron, P. (2006). Multiple Structural Change Models: A Simulation Analysis. In *Econometric Theory and Practice: Frontiers of Analysis and Applied Research, D. Corbea, S. Durlauf and B. E. Hansen (eds.)*, pages 212–237. Cambridge University Press.

Bataa, E., Osborn, D. R., Sensier, M., and Dijk, D. v. (2013a). Identifying Changes in Mean, Seasonality, Persistence and Volatility for G7 and Euro Area Inflation. *Oxford Bulletin of Economics and Statistics*.

Bataa, E., Osborn, D. R., Sensier, M., and van Dijk, D. (2013b). Structural Breaks in the International Dynamics of Inflation. *Review of Economics and Statistics*, 95(2):646–659.

Benati, L. and Kapetanios, G. (2002). Structural Breaks in Inflation Dynamics. Manuscript, Bank of England.

Bernanke, B. S. (2007). *Globalization and Monetary Policy.* Stanford Institute for Economic Policy Research, Stanford, California.

Cecchetti, S. G. and Debelle, G. (2006). Has the inflation process changed? *Economic Policy*, 21(46):311–352.

Census Bureau, U. (2011). *X-12-ARIMA reference Manual.*

Chen, C. and Liu, L.-M. (1993). Joint Estimation of Model Parameters and Outlier Effects in Time Series. *Journal of the American Statistical Association*, 88(421):284–297.

Ciccarelli, M. and Mojon, B. (2010). Global Inflation. *Review of Economics and Statistics*, 92(3):524–535.

Dees, S., Mauro, F. d., Pesaran, M. H., and Smith, L. V. (2007). Exploring the international linkages of the euro area: a global VAR analysis. *Journal of Applied Econometrics*, 22(1):1–38.

Giordani, P., Kohn, R., and van Dijk, D. (2007). A unified approach to nonlinearity, structural change, and outliers. *Journal of Econometrics*, 137(1):112–133.

Hall, A. and Sakkas, N. (2013). Approximate p-values of certain tests involving hypotheses about multiple breaks. *Journal of Econometric Methods.*

Krolzig, H.-M. and Hendry, D. F. (2001). Computer automation of general-to-specific model selection procedures. *Journal of Economic Dynamics and Control*, 25(6–7):831–866.

Levin, A. T. and Piger, J. (2003). Is Inflation Persistence Intrinsic in Industrial Economies? Working Paper No. 2002-023A, Federal Reserve Bank of St. Louis, Rochester, NY.

Monacelli, T. and Sala, L. (2009). The International Dimension of Inflation: Evidence from Disaggregated Consumer Price Data. *Journal of Money, Credit and Banking*, 41:101–120.

Mumtaz, H. and Surico, P. (2012). Evolving International Inflation Dynamics: World and Country-Specific Factors. *Journal of the European Economic Association*, 10(4):716–734.

Neely, C. J. and Rapach, D. E. (2011). International comovements in inflation rates and country characteristics. *Journal of International Money and Finance*, 30(7):1471–1490.

O'Reilly, G. and Whelan, K. (2005). Has Euro-Area Inflation Persistence Changed Over Time? *Review of Economics and Statistics*, 87(4):709–720.

Osborn, D. R. and Ghysels, E. (2001). *The Econometric Analysis of Seasonal Time Series*. Cambridge University Press.

Pesaran, M. H., Schuermann, T., and Weiner, S. M. (2004). Modeling Regional Interdependencies Using a Global Error-Correcting Macroeconometric Model. *Journal of Business & Economic Statistics*, 22(2):129–162.

Pitarakis, J.-Y. (2004). Least squares estimation and tests of breaks in mean and variance under misspecification. *Econometrics Journal*, 7(1):32–54.

Qu, Z. and Perron, P. (2007). Estimating and Testing Structural Changes in Multivariate Regressions. *Econometrica*, 75(2):459–502.

Sensier, M. and van Dijk, D. (2004). Testing for Volatility Changes in U.S. Macroeconomic Time Series. *Review of Economics and Statistics*, 86(3):833–839.

Stock, J. H. and Watson, M. W. (2003). Forecasting Output and Inflation: The Role of Asset Prices. *Journal of Economic Literature*, 41(3):788–829.

Trichet, J.-C. (2008). *Globalisation, inflation and the ECB monetary policy*. Barcelona Graduate School of Economics.

Yao, Y.-C. (1988). Estimating the number of change-points via Schwarz' criterion. *Statistics & Probability Letters*, 6(3):181–189.

Yohei Yamamoto (2012). *m-Break*.