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ARTICLE

Has international CPI inflation comovement strengthened since the global financial crisis?†

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Abstract

This study detects a structural break in international consumer price index (CPI) inflation comovement. We estimate the dynamic common factor models with unknown breakpoints of cross-country inflation rates and global price index of all commodities. We identify two global factors from the models: a commodity global factor and a noncommodity global factor. The former is a common factor between national inflation rates and commodity price index growth; the latter is a common factor among national inflation rates. The estimation of 29 countries' quarterly CPI inflation data from 2001:Q1 to 2018:Q2 shows a one-time break in cross-country inflation dynamics in 2008:Q4. Thereafter, the importance of global factors in explaining the national inflation rates is remarkably increased. Furthermore, the increased global inflation synchronization is mainly driven by the larger role of the noncommodity global factor rather than that of the commodity global factor.

Keywords: Variance decomposition, structural break, financial openness, Bayesian MCMC estimation

JEL Classfications: E31, F41, F62

1. Introduction

Some simple indicators suggest that the degree of global synchronization of national consumer price index (CPI) inflation rates has strengthened since the 2008 global financial crisis (GFC). For example, in a sample of the quarterly inflation series of 29 advanced countries over the period 2001:Q1–2018:Q2, the correlation of national inflation rates with the global inflation rate, measured by the average inflation rate of the G7 countries and China, jumped from 0.30 before the crisis to 0.83 after the crisis on average. In addition, the portions of the first principal component among the national inflation rates are 0.31 and 0.66 before and after the crisis, respectively. Motivated by this observation, the priority of this paper is to examine whether structural changes have occurred in the degree of inflation comovement during the recent decades.[1]

To this end, we employ a dynamic common factor model with Markov regime switching parameters. To construct a model for the national inflation process with global factors, we use the dynamic factor model framework, which is now a standard approach to study global inflation

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synchronization (e.g., Kose et al. (2003, 2008), Neely and Rapach (2011), Förster and Tillmann (2014), Parker (2018), Choi et al. (2018), Kamber and Wong (2020), and Kose et al. (2019)). The basic set-up of the model allows for two global factors, a latent common factor between the global price index of all commodities (commodity price, hereafter) movement and national inflation rates, which we call commodity global factor, and another global factor, which we call noncommodity global factor, to capture all the remaining influences of global sources other than the commodity global factor. The extent to which each global factor explains the cross-country inflation dynamics is quantified by variance decomposition. In addition to the basic specification, we examine two alternative specifications by adding two sets of local factors to check the stability of our empirical findings. The first specification includes a Euro region factor because 13 of the 29 countries in our samples belong to the eurozone. The other specification categorizes the sample countries into two groups based on their economic position in the global economy, namely, the G8 (=G7 + China) economies and the small economies.[2] Each country's inflation is affected by the corresponding group factor in addition to the global factors. Finally, in the model, the loadings of global factors are assumed to change at unknown breakpoints. Our econometric approach is Bayesian. Following Chib (1998) and Chib and Kang (2013), we test the existence of structural breaks in the degree of inflation comovement by imposing the change-point restriction on the transition probabilities of regime shifts.

Our empirical findings can be summarized as follows. First, the cross-country inflation dynamics underwent a one-time break in 2008:Q4 that is robust to all the three specifications.[3] The two global factors are found to account for around 61.6% of the national inflation rates after the break, registering a significant increase from about 46.0% before the break. Second, the noncommodity global factor is found to be a more important driver behind the increase in the inflation synchronization. The portion of the global inflation comovement due to the noncommodity global factor, uncovered by the variance decomposition technique, has increased significantly since the break across the sample. In contrast, empirical evidences for a significant change in the portion of the contribution by the commodity global factor around the break are weak.

To shed some light on the question that naturally arises as to what drove the increase in global inflation comovement in the recent decade, we conduct a diagnostic analysis of the relationship between country characteristics and inflation comovement. Among various country characteristics, we find that the increased global synchronization is positively correlated to the measure for de facto financial openness. Notably, the significance of the financial openness for the change in the inflation comovement is found to be mainly driven by the countries that adopted the unconventional monetary policy (UMP) regime after the GFC. In addition, we find that the global common factors extracted by our model are positively related to the Bank of International Settlement (BIS) indicator for the global liquidity in US dollar with statistical significance after the GFC, but not before the GFC. These empirical results suggest that the adoption of the UMP by major central banks to deal with the large deflationary shock from the GFC, the transmission of the deflationary shock and the spread of the UMP regime to small open economies through capital flows underlie the increase in the inflation comovement since the GFC.

Our study is related to the growing literature on the international comovement of inflation. Existing studies tend to establish that the international comovement of inflation across industrialized countries has been a persistent characteristic in the second half of the last century. Ciccarelli and Mojon (2010) document the presence of inflation comovement across 22 OECD countries since the 1960s by showing that their global factor measures substantially explain the national inflation movement. Mumtaz and Surico (2012) use the dynamic factor model framework and examine the inflation rates of 11 advanced economies, to come to similar conclusions. Neely and Rapach (2011) extend the analysis to 64 countries, including the developing economies, and confirm the importance of global factors in national inflation.[4] The lack of data points after the global financial crisis of 2008 naturally stalls these studies from investigating any change in the post-global financial crisis era. Moreover, not all of these studies are designed for formal testing of structural changes in the national inflation processes associated with global factors. More recently,

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Bataa et al. (2013) and Altansukh et al. (2017) examine the structural breaks in international inflation relationships using a conventional vector autoregression framework. From the nature of the VAR framework, their studies consider a limited number of countries, specifically the G7 or 13 OECD economies. Both studies are geared to assess the developments before the global financial crisis.

Our study differs from this line of literature mainly in that we specifically test for the presence of structural breaks in the global inflation comovement, focusing on the recent two decades. The inflation series in most of the countries showed a downward trend in the 1980s and 1990s, but not in the recent two decades.[5] To implement a structural test with a sample of a longer time span, one has to decide whether and how to control the trends in the data. The dynamics in the trends and cyclical components identified can differ substantially depending on the researcher's methodologies such as whether to incorporate time-varying volatility and how to resolve the pile-up problem associated with identifying the inflation trends.[6] By focusing on the recent two decades, we can avoid the methodological complications.

As evidences for the inflation comovement accumulate, Förster and Tillmann (2014) and Parker (2018) explore a source of the comovement by investigating whether the role of global factors differs between commodity and noncommodity prices. In a similar vein, Kamber and Wong (2020) examines the relative role of global commodity and noncommodity factors in dictating national inflation processes. They generally find that commodity prices drive global inflation comovement. Our study contributes to this line of literature by showing not only that the global inflation comovement has been further strengthened since the great financial crisis but also that the driving force behind the comovement has been switched from the commodity to the noncommodity factor.

In particular, Kamber and Wong (2020) examine the relative role of commodity and the noncommodity shocks with the sample including data points up to the first quarter of 2018, which is similar to our sample period. Their empirical modeling does not allow for structural breaks. Thus, their conclusion regarding the role of noncommodity and commodity global shocks are based on the whole sample period, while our focus is on the relative changes between the pre-GFC and the post-GFC period. Another key difference of our study from theirs concerns the coverage of the sample. Their sample mainly consists of emerging economies, excluding G7 economies except Canada and countries in the eurozone. To the extent that the noncommodity global factor uncovered by our model is dominated by the inflation movement of these countries, Kamber and Wong (2020)'s estimates of the noncommodity global factor may differ from ours.

To our knowledge, the structural break in global inflation synchronization that we observe around the global financial crisis of 2008 is a new finding. This implies that neglecting the structural change can lead to misunderstanding of each country's national inflation dynamics, which in turn could hinder proper monetary policy-making. A related new finding is that the noncommodity factor, rather than commodity factor, is the driving force behind higher comovement.

The remainder of this paper is organized as follows. The next section describes the data used. Section 3 presents our econometric framework for dynamic factor models with unknown breakpoints. Section 4 discusses our empirical findings and explores the underlying forces behind the results. Finally, Section 5 concludes the paper.

2. Data

2.1 Inflation rates

For inflation data, we use the quarterly CPI aggregate inflation series of 29 countries for the first quarter of 2001 to the second quarter of 2018 period. For the list of countries, see Table 1. These countries are selected based on availability of quarterly CPI inflation rates data for the sample period. All the inflation data are taken from the OECD Main Economic Indicators database.

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Table 1. List of countries. This table presents the list of the countries in each group. The time span is from 2001:Q1 to 2018:Q2. The source of data is the OECD database

Category	Countries
G8 countries	Canada(G8), France(Euro), Italy(G8, Euro), Japan, Germany(Euro), United States, United Kingdom, China
Advanced small countries	Australia, Austria(Euro), Belgium(Euro), Czech Republic, Denmark, Finland(Euro), Greece(Euro), Iceland, Ireland(Euro), Israel, Korea, Latvia, Luxembourg(Euro), Netherlands(Euro), New Zealand, Norway, Portugal(Euro), Slovak Republic(Euro), Spain(Euro), Sweden, Switzerland

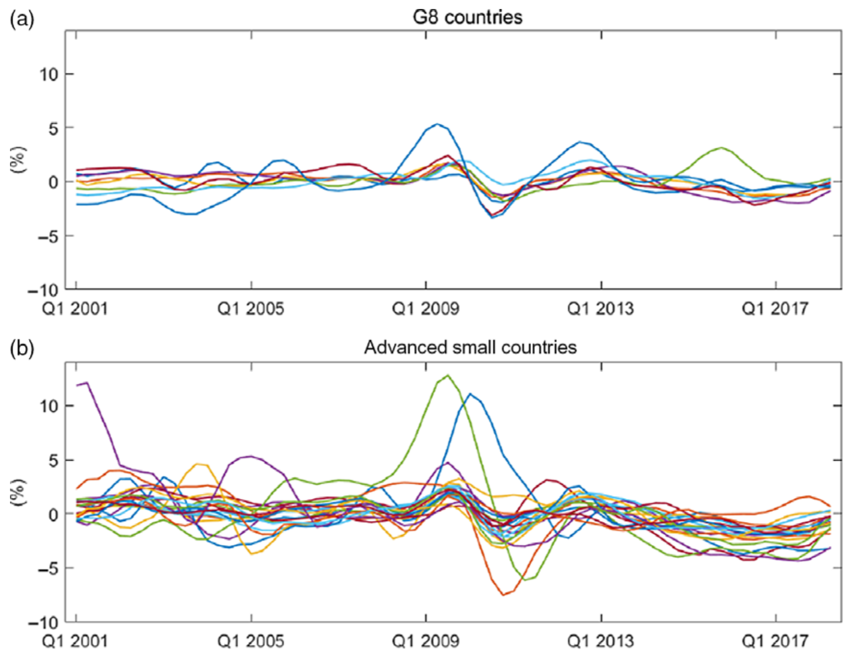

Figure 1. Cross-country CPI inflation rates. This figure plots the time series of the demeaned year-to-year cross country CPI inflation rates from the first quarter of 2001 to the second quarter of 2018.

The countries in the sample can be classified in several ways. Our sample includes 29 advanced economies classified according to the IMF classification, grouping them by economic development status. The sample includes all the large G8 economies. In addition, 13 countries in the sample are from the Euro area.[7]

Figure 1 plots the time series of the quarterly CPI inflation rates of 29 countries for the sample period. For the purpose of diagnostic investigation, the countries are divided into two groups: the G8 and advanced small countries. The inflation rates of the G8 are the most stable, showing the smallest cross-country variation.

2.2 Global commodity price

We use the global price index of all commodities as a measure of the global commodity price. The global price index of all commodities is a composite of energy, edibles, agricultural raw materials, and metals prices, and it can be obtained from the Federal Reserve Economic Data of St. Louis Fed. We regard the global commodity price index as an empirical proxy of the common factor among

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various commodity prices on the presumption that the index is designed to efficiently reflect the condition of the commodity markets.

2.3 Country characteristics

For the analyses in Section 4, we consider four country characteristics, namely, trade openness, financial openness, fixed exchange rate regime, and central bank transparency. We measure the trade openness of a country by its merchandise imports and exports to GDP ratio based on data from the Penn World Table. Imports and exports are quantified in US dollars based on purchasing-power-parity exchange rates. Financial openness is measured as the ratio of the sum of countries' international assets and liabilities to GDP, following Lane and Milesi-Ferretti (2007), for which an updated data set is available up to 2015. For the measure of fixed exchange rate regime, we take the de facto fixed exchange rate regime index data set from Shambaugh (2004), for which an updated version is available up to 2014. Finally, the central bank transparency index is taken from Dincer and Eichengreen (2014). The data for some of the measures are not available for later years of the sample period.

As shown later, our regression requires only average values of the four country characteristic measures over the pre- and post-break subperiods. For consistency, we compute the average values of the pre- and post-break subperiod measures using the data of five years close to the breakpoint. Anticipating the results from the dynamic common factor models with unknown changepoints, we find a one-time structural break in 2008. Thus, to compute the five-year average values, we use data from 2003 to 2007 for the pre-break subperiod, and data from 2009 to 2013 for the post-break subperiod.

3. Econometric framework

3.1 Conditional Gaussian dynamic common factor models with unknown structural breakpoints

We now describe our dynamic common factor models with structural breaks. Our key idea is to combine the dynamic common factor methodology with Markov-Switching structural breaks modeling. We begin by explaining how to identify structural breaks. We model structural breaks as a change-point process, as detailed in Chib (1998). Specifically, we assume that the loadings of the common factors specified below are subject to stochastic regime changes at unknown points, where the change points can be described as a restricted first-order Markov process. Under this assumption, when $s_t(=1, 2, .., J)$ is a regime indicator at time t and J denotes the total number of regimes, the economies can either stay at the current regime or move to the next regime with a certain probability. Formally, when $s_t = j$, the next-period regime indicator s_{t+1} either takes the current value (regime continues) so that $s_{t+1} = j$ with a probability of p_{jj}, or jumps to the next regime (regime changes) so that $s_{t+1} = j + 1$ with a probability of $(1 - p_{jj})$. It can never return to a previous regime or jump to regimes $j + 2$, $j + 3$, ., , J. The final regime J is absorbing.

Commodity prices are an obvious source of global inflation synchronization. In view of this, we try to decompose the shocks from global origin into commodity-related and noncommodity-related ones. To do so, we include the commodity inflation series as well as national inflation in our model. In terms of the modeling strategy that allows multiple global factors in a dynamic common factor model, our approach is similar to Förster and Tillmann (2014) and Parker (2018).

Our dynamic common factor model has three specifications depending on the number of group factors we allow. We experiment with three sets of group factors. The basic setup does not have a group factor, the second one has the Euro region factor, while the third set comprises two group factors—the G8 country group and advanced small country group. For the sake of convenience, we begin with the third specification.

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3.1.1 Two-global and two-group factor model

In this specification, referred to as $\mathcal{M}_{2G}$, we assume that five factors drive the cross-country inflation dynamics of the sample: four common factors and one country-specific factor. In the equations below, x_t denotes the global commodity price index growth. The vectors of the G8 inflation rates and advanced and developing countries' inflation rates $\pi_t^{G8}$and π_t^A, respectively. The first two common factors (G_t^C, G_t^{NC}) are global, affecting the inflation rates of all countries. G_t^C, which we define as the commodity global factor, is identified as a latent factor between all the national inflation rates and commodity price growth. G_t^{NC} corresponds to the noncommodity global factor, identified as a latent factor affecting all the national inflation rates, but orthogonal to the commodity global factor. The two group factors are assumed to affect only certain countries in the sample. The G8 ($G8_t$) and advanced (A_t) country factors are assumed to influence only the G8 and advanced small country inflation rates, respectively. Given the regimes and common factors, the commodity price growth and inflation rates are assumed to be generated from conditional Gaussian distribution:

$$\underbrace{\begin{pmatrix} x_t \\ \pi_t^{G8} \\ \pi_t^A \end{pmatrix}}_{y_t} = \underbrace{\begin{bmatrix} \delta_{s_t}^x & 0 & 0 & 0 \\ \delta_{s_t}^{G8} & \gamma_{s_t}^{G8} & \mu_{s_t} & 0_{8\times 1} \\ \delta_{s_t}^A & \gamma_{s_t}^A & 0_{M_A\times 1} & \kappa_{s_t} \end{bmatrix}}_{\Gamma_{s_t}} \times \underbrace{\begin{pmatrix} G_t^C \\ G_t^{NC} \\ G8_t \\ A_t \end{pmatrix}}_{\mathbf{f}_t} + \underbrace{\begin{pmatrix} \varepsilon_t^X \\ \varepsilon_t^{G8} \\ \varepsilon_t^A \end{pmatrix}}_{\varepsilon_t}.$$

The factor loading Γ_{s_t} is regime-dependent and captures the changes in the role of common factors in each inflation rate. Each common factor is assumed to follow a first-order autoregressive process, with the factors mutually uncorrelated. The factor process can be expressed as

$$\begin{aligned} \mathbf{f}_t|\mathbf{f}_{t-1}, \Phi &\sim \mathcal{N}(\Phi\mathbf{f}_{t-1}, I_4), \\ \mathbf{f}_0|\Phi &\sim \mathcal{N}(0, (I_4 - \Phi^2)^{-1}), \end{aligned}$$

where the first-order autoregressive (AR(1)) coefficient matrix Φ is a 4×4 diagonal matrix, I_k is a k-dimensional identity matrix, and the conditional variance-covariance is limited to an identify matrix for identification. Finally, ε_t^X is the commodity price factor, and ε_t^{G8} and ε_t^A are individual country-specific factors independent of common factors. The components in ε_t are also assumed to follow the mutually independent AR(1) processes,

$$\begin{aligned} \varepsilon_t^X|\varepsilon_{t-1}^X, \psi^X, \Sigma^X &\sim \mathcal{N}(\psi^X\varepsilon_{t-1}^X, \Sigma^X),\ \varepsilon_t^{G8}|\varepsilon_{t-1}^{G8}, \psi^{G8}, \Sigma^{G8} \sim \mathcal{N}(\psi^{G8}\varepsilon_{t-1}^{G8}, \Sigma^{G8}), \\ \varepsilon_t^A|\varepsilon_{t-1}^A, \psi^A, \Sigma^A &\sim \mathcal{N}(\psi^A\varepsilon_{t-1}^A, \Sigma^A), \end{aligned}$$

given the diagonal matrices of the AR coefficients and conditional variances. Like the common factors, each initial country-specific factor at time 0 is assumed to be generated from its unconditional distribution.

3.1.2 Two-global and one-Euro factor model

Given that 13 countries out of the 29 are from the eurozone, we consider an alternative model specification $\mathcal{M}_{Euro}$, which includes the euro factor (E_t). The eurozone countries are France, Germany, Italy, Austria, Belgium, Greece, Finland, Ireland, Luxembourg, Netherland, Portugal, Slovakia, and Spain. The eurozone and non-eurozone country inflation rates are denoted by π_t^E and π_t^{NE}, respectively. The non-eurozone country inflation rates are generated from the two global and country-specific factors, while the eurozone country inflation rates are determined by the euro factor as well as the global and country-specific factors. The resulting measurement equation

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is given by

$$\begin{pmatrix} x_t \\ \pi_t^{NE} \\ \pi_t^{E} \end{pmatrix} = \begin{bmatrix} \delta_{s_t}^{x} & 0 & 0 \\ \delta_{s_t}^{NE} & \gamma_{s_t}^{NE} & 0_{28\times 1} \\ \delta_{s_t}^{E} & \gamma_{s_t}^{E} & \mu_{s_t}^{E} \end{bmatrix} \begin{pmatrix} G_t^{C} \\ G_t^{NC} \\ E_t \end{pmatrix} + \begin{pmatrix} \varepsilon_t^{X} \\ \varepsilon_t^{NE} \\ \varepsilon_t^{E} \end{pmatrix}.$$

As in model $\mathcal{M}_{2G}$, the common factors and country-specific factors are assumed to follow AR(1) processes.

3.1.3 Two-global factor model

We also simulate global factors from a model without local common factors. That is, all inflation rates are decomposed into two global factors and one country-specific factor following AR(1) processes. Thus, this simple model $\mathcal{M}_0$ expressed as

$$\begin{pmatrix} x_t \\ \pi_t \end{pmatrix} = \begin{bmatrix} \delta_{s_t}^{x} & 0 \\ \delta_{s_t} & \gamma_{s_t} \end{bmatrix} \begin{pmatrix} G_t^{C} \\ G_t^{NC} \end{pmatrix} + \begin{pmatrix} \varepsilon_t^{X} \\ \varepsilon_t^{\pi} \end{pmatrix},$$

is a restricted specification of models $\mathcal{M}_{2G}$ and $\mathcal{M}_{Euro}$.

3.2 Prior distribution

We complete our Bayesian modeling by specifying prior distributions for the model parameters. Given our prior belief that the regimes are persistent and structural breaks occur at a low frequency, we assume that the transition probability p_{jj} for $j = 1, 2, .., N-1$ follows a beta distribution, $beta(a_{j,j} = 48, a_{j,j+1} = 2)$. Next, we assume that the priors for all the factor loading coefficients in $(\delta_{s_t}^{X}, \delta_{s_t}^{G8}, \delta_{s_t}^{A}, \gamma_{s_t}^{G8}, \gamma_{s_t}^{A}, \mu_{s_t}, \kappa_{s_t}, \lambda_{s_t})$ of model $\mathcal{M}_{2G}$ are not regime-specific, implying that regime changes are detected by the information contained in the data, not the prior. In addition, because we believe that the cross-country inflation rates are positively correlated on average, we consider the prior mean of each parameter positive. However, as our prior belief is not strong, the prior distribution of each factor loading parameter is chosen as $\mathcal{N}(0.5, 4)$.

Year-to-year inflation rates are known to be typically persistent. This persistence can be explained by the weak mean-reverting property of the common factors. Thus, all AR coefficients in Φ are distributed as $\mathcal{N}(\bar{\Phi} = 0.8, V^{\Phi} = 0.04)$ a priori. Meanwhile, because country-specific components are believed to be relatively less persistent, the prior for the corresponding AR coefficients is chosen as $\mathcal{N}(\bar{\psi} = 0.4, V^{\psi} = 0.04)$. We assume that the variances in Σ are generated from the inverse gamma distribution, $\mathcal{IG}(\bar{\nu} = 4, \bar{\delta} = 0.2)$. Finally, for models $\mathcal{M}_0$ and $\mathcal{M}_{Euro}$, we assume the same prior for the factor loading coefficients and parameters in AR(1) factor processes.

3.3 Posterior sampling

We denote the model parameters and time series of the observations, factors, and regimes by θ, $\mathbf{y} = \{y_t\}_t^T$, $\mathbf{F} = \{\mathbf{f}_t\}_{t=1}^T$, and $\mathbf{S} = \{s_t\}_{t=1}^T$, respectively, where all observations are demeaned and standardized to have variance of 4. Given the joint model for cross-country inflation rates and commodity price and the priors for model parameters, we estimate the models with different number of regimes by sampling the joint posterior distribution of the parameters, factors, and regimes,

$$\theta, \mathbf{F}, \mathbf{S} | \mathbf{y}.$$

Because posterior sampling is done in a multiple block, the Gibbs sampling scheme can be applied. Specifically, factor loadings, the parameters in the factor processes, regimes, factors, and transition

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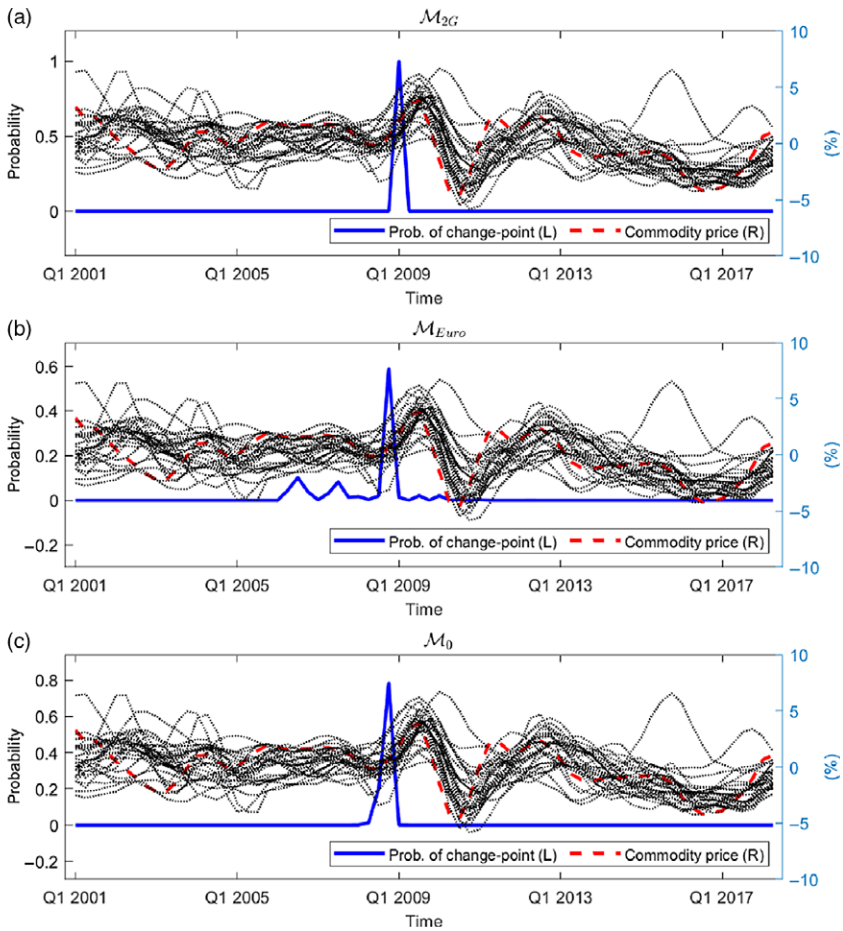

Figure 2. Posterior probabilities of breakpoint. This figure plots the posterior probabilities of the breakpoint across three dynamic common factor models. The dashed line is the global commodity price index growth, and the dotted lines in panels (a), (b), and (c) are the cross-country inflation rates. All observations are demeaned.

probabilities are sequentially simulated from their full conditional distributions in each MCMC cycle. The detailed procedure of each block is provided in Appendix A.

4. Estimation results

4.1 Breakpoints

Figure 2 displays the posterior probabilities of the breakpoint estimated from dynamic common factor models. The models $\mathcal{M}_{2G}$ and $\mathcal{M}_0$ produce a one-time sharp regime change in the fourth quarter of 2008, and the posterior mode of the breakpoint from model $\mathcal{M}_{Euro}$ is estimated in the first quarter of 2009. The models with one breakpoint are strongly preferred to those with no breakpoint, because the difference in the BICs exceeds 50.78.[8] Furthermore, the models allowing for more than one structural breaks also produce only one-time break, with the result that the one-time breakpoint is most supported in the data.[9]

Since all the model parameters can simultaneously change, there could be a case where the structural break is driven by a particular group of countries, rather than by all the three groups. To examine whether a break is sensitive to the inclusion of countries, we estimate two additional $\mathcal{M}_0$

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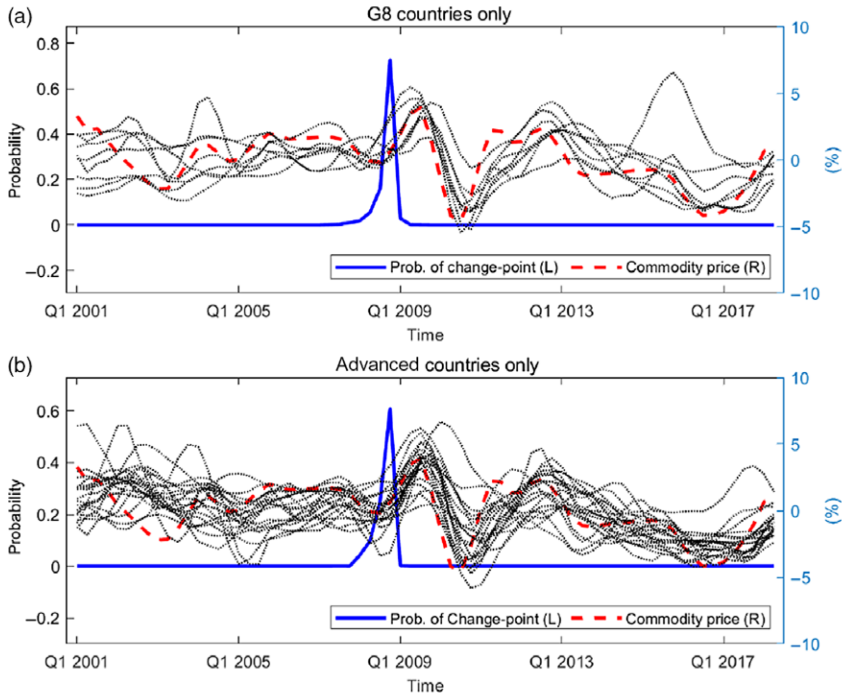

Figure 3. Posterior breakpoint probabilities: group-wise analysis. This figure plots the posterior breakpoint probabilities estimated from three two-global factor models: the models for the G8 countries only and advanced countries only. The dotted lines in panels (a) and (b) represent the inflation rates of the G8 countries and advanced small countries, respectively.

models—the models of the G8 countries only and advanced small countries only. The commodity price growth is included in these models. The posterior probabilities of a breakpoint from group-wise analysis are provided in Figure 3. This figure confirms that the inflation data of all the country groups contribute to a one-time change around the financial crisis. Consequently, the structural break in cross-country CPI inflation dynamics is robust to both model specification and country groups.

4.2 Variance decomposition

Given the strong evidence of one-time break in cross-country inflation dynamics, we discuss the driving nature of the change. For this, we compare the variance-decompositions before and after the break, focusing on the global factor portions. Figure 4 presents the posterior commodity and noncommodity global factor estimates over time across models. One noticeable feature is the substantially differing dynamics across the models before the break that become similar after the break. Thus, the global factors are found to be more robust to model specifications during the post-crisis than pre-crisis period.

Tables 2, 3, and 4 report the variance decomposition results. Figures 5, 6, and 7 also present the posterior means and 90% credibility intervals of the variance decomposition. These tables and figures show two interesting results that are robust to model specification. First, the global inflation comovement is not limited to the G8, with the global factors showing increasing effects on the advanced small countries' inflation rates. Taking the results of model $\mathcal{M}_{2G}$, the global factor portions increased for all but two G8 countries and 4 advanced countries among 29 countries. The average portion explained by the global factors increased from 46.0% to 61.6% after the break. Similarly, the global factor portions for the G8 countries also remarkably increased from 47.6% to

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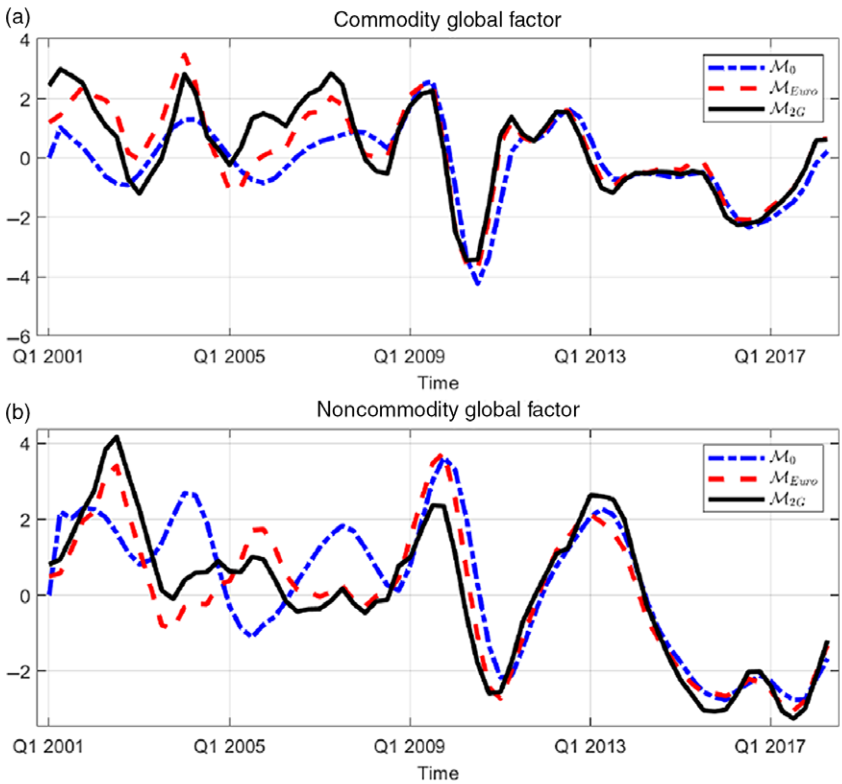

Figure 4. Global factors. This figure plots the posterior means of dynamic common factors over time based on 5000 posterior draws.

66.9% on average. The portions for the advanced countries were 45.4% before the break and 59.6% after the break on average.[10] This finding is quite consistent with the recent work of Kabukçuoğlu and Martínez-García (2018), in which they find that global inflation is much more relevant for explaining national inflation rates than output gaps.

Second, the relative importance of the commodity and noncommodity global factors differs across the country groups. To show this, we regress the changes in global factor portions across countries on the constant and G8 country dummies. The coefficient of the dummy variable capture the additional changes in global factor effects on the G8 countries' inflation rates. The results are given in Table 5. The log changes in portion of the two global factors are denoted by ΔVAR_{Total}. The intercept terms in the regression of ΔVAR_{Total} are statistically significant regardless of model specification, with insignificant positive coefficients of the G8 country dummy. It confirms that the inflation comovement has increased for all economies in the sample, not confined to the large.

Now to distinguish the role of the noncommodity factor from the commodity, we repeat the regression separately for the log changes in the effects of the noncommodity global factor (ΔVAR_{NC}) and the commodity (ΔVAR_C). The regression results of ΔVAR_{NC} are similar to those of ΔVAR_{Total}. No estimates of the coefficient to the G8 dummy variable are significant for ΔVAR_{NC} across the three specifications, while the intercept terms are estimated significant for all the three. It indicates that the noncommodity global factor has contributed to the increase in the inflation comovement after the break simultaneously across the large and the small open economies. In contrast, the results for ΔVAR_C are mixed depending on the model specification. Estimates are insignificant both for the intercept term and the G8 dummy for $\mathcal{M}_{2G}$. It is significant

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Table 2. Variance decomposition of CPI inflation rates and commodity price: $\mathcal{M}_{2G}$. This table presents the posterior estimates of the variance decomposition of each country's inflation in percentage before and after the break based on 5000 posterior draws

	Global									
Factor	Commodity ($G^C{}_t$)		Non -commodity ($G^{NC}{}_t$)		G8 country ($G8_t$)		Advanced country (A_t)		Country -specific (ε_t)	
Regime	1	2	1	2	1	2	1	2	1	2
Commodity price	67.7	92.8	0.0	0.0	0.0	0.0	0.0	0.0	32.3	7.2
(a) G8 countries										
Canada	46.7	33.1	18.2	17.9	8.7	23.1	0.0	0.0	26.4	25.9
France	37.8	39.5	29.7	51.3	8.1	2.2	0.0	0.0	24.4	7.0
Germany	8.4	37.2	42.6	44.4	22.7	2.7	0.0	0.0	26.3	15.7
Italy	24.0	12.6	40.8	81.8	4.8	1.1	0.0	0.0	30.5	4.5
Japan	10.8	8.5	7.8	7.1	7.0	64.8	0.0	0.0	74.5	19.6
United Kingdom	4.2	18.7	7.4	40.2	5.2	11.7	0.0	0.0	83.1	29.4
United States	46.1	72.7	23.9	10.4	5.8	8.5	0.0	0.0	24.3	8.4
China	7.2	50.6	25.8	9.1	17.8	2.1	0.0	0.0	49.2	38.2
(b) Advanced small countries										
Australia	23.2	38.5	27.3	13.1	0.0	0.0	19.4	14.5	30.1	33.9
Austria	15.3	43.2	36.5	35.5	0.0	0.0	15.8	5.1	32.3	16.1
Belgium	9.9	23.1	26.0	51.5	0.0	0.0	5.6	11.8	58.4	13.7
Czech Republic	4.6	9.9	44.2	50.0	0.0	0.0	2.8	3.2	48.5	37.0
Denmark	30.6	20.7	12.3	60.4	0.0	0.0	3.4	5.0	53.7	13.8
Finland	11.3	11.4	23.1	49.7	0.0	0.0	10.7	26.2	54.9	12.7
Greece	10.9	28.4	11.6	37.1	0.0	0.0	5.5	2.1	72.1	32.4
Iceland	5.2	6.6	10.3	20.4	0.0	0.0	2.6	23.9	81.9	49.1
Ireland	13.6	15.9	14.2	48.0	0.0	0.0	8.8	13.5	63.5	22.6
Israel	40.8	11.8	7.4	10.4	0.0	0.0	9.5	10.5	42.3	67.3
Korea	12.6	18.1	57.6	33.6	0.0	0.0	2.2	25.9	27.6	22.4
Latvia	5.2	3.3	14.9	44.5	0.0	0.0	3.2	21.6	76.7	30.6
Luxembourg	48.2	47.6	28.9	47.8	0.0	0.0	6.0	0.7	16.9	4.0
Netherlands	5.9	7.2	35.8	49.3	0.0	0.0	11.1	5.3	47.2	38.2
New Zealand	33.2	27.8	13.4	11.9	0.0	0.0	17.6	37.4	35.8	22.9
Norway	32.0	8.7	20.2	3.7	0.0	0.0	2.2	27.5	45.6	60.2
Portugal	20.4	16.7	36.2	63.2	0.0	0.0	5.6	2.1	37.7	17.9
Slovak Republic	3.9	3.8	12.1	61.1	0.0	0.0	67.3	7.6	16.6	27.5
Spain	45.8	42.6	29.9	47.9	0.0	0.0	3.8	1.2	20.5	8.4
Sweden	12.2	31.3	40.8	29.4	0.0	0.0	2.3	23.0	44.7	16.3
Switzerland	44.4	60.7	21.8	6.0	0.0	0.0	2.8	20.2	30.9	13.2

for the intercept term for the model of $\mathcal{M}_0$, but only for the G8 dummy for $\mathcal{M}_{Euro}$. Altogether the evidence for whether the commodity global factor has induced the structural break in the inflation comovement is unclear. In other words, it is the noncommodity global factor rather than the commodity that has played a more important role in strengthening the global inflation comovement.

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Table 3. Variance decomposition of CPI inflation rates and commodity price: $\mathcal{M}_{Euro}$. This table presents the posterior estimates of the variance decomposition of each country's inflation in percentage before and after the break based on 5000 posterior draws

Factor	Global: Commodity ($G_t{}^C$)		Global: Non-commodity ($G_t{}^{NC}$)		EU country (E_t)		Country-specific (ε_t)	
Regime	1	2	1	2	1	2	1	2
Commodity price	42.1	84.4	0.0	0.0	0.0	0.0	57.9	15.6
(a) G8 countries								
Canada	53.1	37.7	21.7	26.1	0.0	0.0	25.2	36.2
France	26.5	44.1	26.3	31.2	5.4	11.8	41.9	12.9
Germany	10.0	39.7	44.2	24.3	8.0	14.8	37.8	21.3
Italy	17.3	16.8	23.5	47.4	6.1	21.6	53.1	14.1
Japan	6.2	15.0	7.4	27.7	0.0	0.0	86.4	57.3
United Kingdom	7.8	17.3	11.1	51.7	0.0	0.0	81.1	31.0
United States	36.2	74.1	26.6	11.4	0.0	0.0	37.3	14.5
China	8.0	48.4	30.1	10.4	0.0	0.0	61.9	41.3
(b) Advanced small countries								
Australia	33.6	37.1	25.8	21.3	0.0	0.0	40.6	41.7
Austria	15.5	45.2	32.3	29.1	17.4	6.9	34.8	18.9
Belgium	8.9	25.5	24.0	49.2	7.3	7.1	59.8	18.2
Czech Republic	8.7	17.5	38.5	40.5	0.0	0.0	52.8	42.0
Denmark	30.0	25.0	9.5	50.0	0.0	0.0	60.5	25.0
Finland	17.9	13.1	17.1	63.3	8.5	3.3	56.5	20.3
Greece	10.9	25.7	9.2	15.2	4.6	18.5	75.4	40.6
Iceland	7.7	5.6	10.4	41.5	0.0	0.0	81.9	53.0
Ireland	20.0	16.4	11.5	39.6	5.1	10.8	63.4	33.2
Israel	40.6	13.3	11.9	15.4	0.0	0.0	47.5	71.3
Korea	15.1	18.7	56.1	52.8	0.0	0.0	28.7	28.5
Latvia	7.3	5.6	12.2	56.8	0.0	0.0	80.6	37.6
Luxembourg	34.4	48.7	24.0	22.3	4.4	18.8	37.2	10.2
Netherlands	6.3	7.1	24.3	32.3	14.0	12.0	55.4	48.6
New Zealand	31.9	27.9	14.1	34.2	0.0	0.0	53.9	37.9
Norway	34.9	10.2	20.5	12.5	0.0	0.0	44.6	77.3
Portugal	26.1	18.3	25.9	29.7	5.0	25.1	43.0	26.9
Slovak Republic	8.1	4.4	18.1	33.7	46.7	11.1	27.2	50.9
Spain	38.2	41.8	25.5	22.6	3.5	20.5	32.7	15.1
Sweden	16.4	33.2	27.5	43.9	0.0	0.0	56.1	22.8
Switzerland	32.3	60.7	20.9	17.2	0.0	0.0	46.8	22.1

4.3 Factor loadings versus factor shock variances

Here we examine whether changes in variance decompositions can be attributed to shifts in the loadings in each country or shifts in the factor variances. For this, we estimate a heteroskedastic model, in which the factor loadings across countries are constant but the variances of common factors are subject to change at unknown data points. The heteroskedastic model is a restricted

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Table 4. Variance decomposition of CPI inflation rates and commodity price: $\mathcal{M}_0$. This table presents the posterior estimates of the variance decomposition of each country's inflation in percentage before and after the break based on 5000 posterior draws

Factor	Global: Commodity ($G_t{}^C$)		Global: Non -commodity ($G_t{}^{NC}$)		Country -specific (ε_t)	
Regime	1	2	1	2	1	2
Commodity price	7.9	82.7	0.0	0.0	92.1	17.3
(a) G8 countries						
Canada	22.8	47.0	24.8	22.3	52.3	30.7
France	11.8	49.9	11.7	42.8	76.5	7.3
Germany	27.4	48.0	26.7	37.6	45.9	14.4
Italy	10.8	20.1	12.7	69.9	76.5	10.0
Japan	2.3	16.0	2.8	17.4	94.9	66.6
United Kingdom	3.3	17.9	3.9	44.8	92.8	37.3
United States	23.5	77.1	23.3	11.8	53.2	11.1
China	12.4	57.1	14.9	9.4	72.7	33.6
(b) Advanced small countries						
Australia	26.1	49.3	27.1	21.4	46.8	29.3
Austria	24.3	52.3	24.0	34.7	51.7	13.0
Belgium	9.0	31.7	10.0	54.6	81.1	13.8
Czech Republic	21.6	21.0	22.4	53.6	56.0	25.4
Denmark	13.6	25.2	19.5	58.1	66.9	16.7
Finland	6.4	20.0	8.4	61.0	85.2	19.0
Greece	2.2	33.6	2.7	17.7	95.1	48.7
Iceland	4.5	7.3	4.7	43.2	90.8	49.4
Ireland	6.2	26.5	9.3	39.6	84.4	33.9
Israel	14.7	11.9	19.4	21.2	65.9	66.9
Korea	23.5	19.1	21.0	52.1	55.6	28.7
Latvia	3.1	8.4	4.2	56.2	92.7	35.4
Luxembourg	24.3	55.5	24.2	38.5	51.4	6.0
Netherlands	8.8	7.3	10.2	46.6	81.0	46.1
New Zealand	12.5	31.0	15.5	34.3	72.0	34.8
Norway	14.3	11.3	17.4	8.8	68.3	80.0
Portugal	17.6	27.2	20.7	48.4	61.7	24.4
Slovak Republic	5.7	6.6	6.8	26.6	87.5	66.9
Spain	22.1	50.3	23.5	38.8	54.4	10.8
Sweden	6.1	39.4	9.1	39.3	84.8	21.3
Switzerland	10.4	63.2	11.6	11.4	78.1	25.4

version of our model that assumes the same factor loadings across the countries, but the loadings are subject to shift given constant factor variances. Given that $\mathcal{M}_{2G}$ is most preferred among the alternative models in terms of the BIC, we specify and estimate a heteroskedastic version of $\mathcal{M}_{2G}$, which is denoted by $\bar{\mathcal{M}}_{2G}$. The measurement equation is given by

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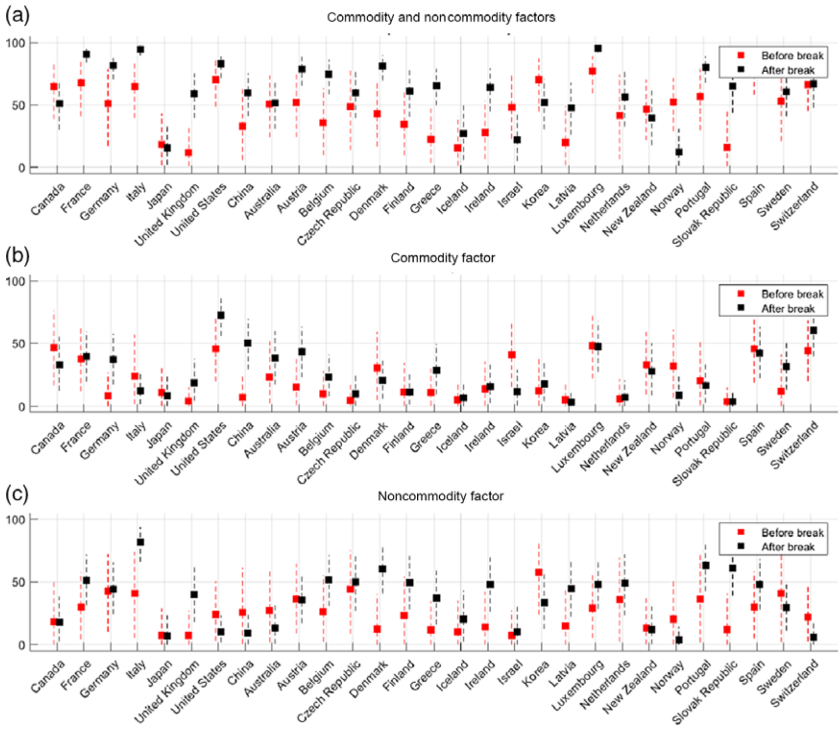

Figure 5. Variance decomposition: $\mathcal{M}_{2G}$ The dashed lines indicate 90% posterior credibility intervals. The red and black markers are the posterior means before and after the break, respectively.

$$\begin{pmatrix} x_t \\ \pi_t^{G8} \\ \pi_t^{A} \end{pmatrix} = \begin{bmatrix} \delta^x & 0 & 0 & 0 \\ \delta^{G8} & \gamma^{G8} & \mu & 0_{8\times 1} \\ \delta^A & \gamma^A & 0_{M_A\times 1} & \kappa \end{bmatrix} \times \begin{pmatrix} G_t^C \\ G_t^{NC} \\ G8_t \\ A_t \end{pmatrix} + \begin{pmatrix} \varepsilon_t^X \\ \varepsilon_t^{G8} \\ \varepsilon_t^A \end{pmatrix},$$

and the common factors follow a first-order autoregressive process with a regime-specific volatility,

$$\mathbf{f}_t|\mathbf{f}_{t-1}, \Phi \sim \mathcal{N}(\Phi\mathbf{f}_{t-1}, \Sigma_{s_t}^F),$$

where $\Sigma_{s_t}^F$ is regime-dependent and is constrained to be diagonal. Each factor shock variance follows an inverse-gamma distribution, $\mathcal{IG}(\bar{\nu} = 4, \bar{\delta} = 0.2)$. The country-specific factor process and prior distributions for the other parameters are assumed to be the same as in $\mathcal{M}_{2G}$.

Figure 8 plots the posterior distributions of the global factor shock volatilities. This reveals a drastic jump in the factor shock volatilities, which seems more pronounced in the commodity factor shock volatility. The BICs of $\mathcal{M}_{2G}$ and $\bar{\mathcal{M}}_{2G}$ are 3815.54 and 44,270.55, respectively. This BIC comparison strongly favors the model $\mathcal{M}_{2G}$, although the heteroskedastic model is more parsimonious. Figure 9 exhibits the country-specific factor loading estimates across regimes. The unrestricted model can accommodate the cross-country heterogeneity of changes in the degree of comovement, as shown by the figure. We can conclude that changes in variance decompositions are due to shifts in factor loadings in each country rather than shifts in factor variances.

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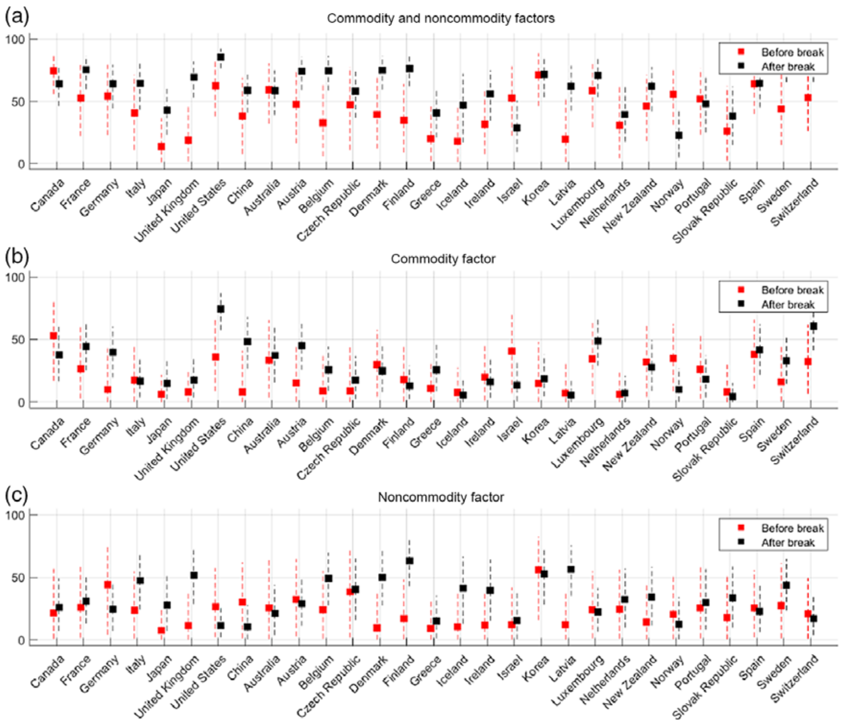

Figure 6. Variance decomposition: $\mathcal{M}_{Euro}$ The dashed lines indicate 90% posterior credibility intervals. The red and black markers are the posterior means using the data before and after the break, respectively.

4.4 Discussion

What would be the driving force behind the increase in inflation comovement after the GFC and the larger role of the global noncommodity factor? To address the question, we begin with a diagnostic analysis of the relationship between country characteristics and inflation comovement. Starting with the widely shared presumption in the literature (Borio and Filardo (2007), Auer and Saure (2013), Bianchi and Civelli (2015), and Ciccarelli and Mojon (2010)) that the degree of international inflation comovement of a country is related to the extent of its linkage to global markets, with the nature of its exchange rate system, and with the extent of similarity of its monetary policy framework to major economies, we selected four country characteristics: (de facto) trade openness, (de facto) financial openness, fixed exchange rate regime, and central bank transparency. Our measurement of these four country characteristics is described in Section 3 above. We regress our measure for the change in the inflation comovement on the changes in the four country characteristic variables between the break.

The change in financial openness is estimated to have a statistically significant relationship with the increase in inflation comovement. The rest of the characteristics show insignificant estimates for the increase in inflation comovement between the breakpoints.[11] How should the positive correlation between changes in the inflation comovement and changes in de facto financial openness or capital flows be interpreted? Our conjecture is that adoption of the UMP by a number of countries in the post-break period may be an underlying element. To explore the plausibility of this conjecture, we examine whether the increase in inflation comovement is more noticeable in the economies that adopted the UMP regime after the GFC. To this end, we identify the UMP using the following two criteria: (1) the lowering of the policy rate to the effective lower bound and (2) the implementation of nonstandard policy tools such as the negative interest rate policy

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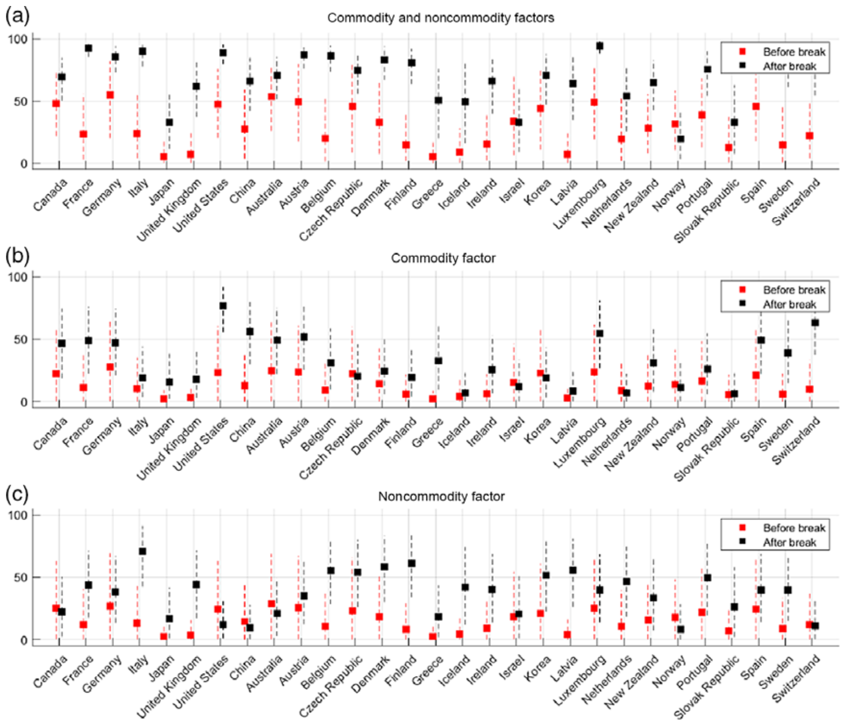

Figure 7. Variance decomposition: $\mathcal{M}_0$ The dashed lines indicate 90% posterior credibility intervals. The red and black markers are the posterior means using the data before and after the break, respectively.

and quantitative easing (QE) measures. In constructing the UMP dummy variable, we draw on the survey collected in BIS (2019) as the first source of information, which we augment with the public information on the website of each central bank.

Then, we regress the change in the inflation comovement on the UMP dummy, financial openness, and the interaction term between financial openness and the UMP dummy. The results are presented in Table 6. We find a positive and statistically significant relationship between the UMP dummy and the change in the inflation comovement for the noncommodity factor, but not for the commodity factor. Moreover, the significance of financial openness for the change in the inflation comovement due to the global noncommodity factor is found to be mainly driven by countries under the UMP regime.

It is well known that the UMP was initially adopted by major central banks such as the Fed and the European Central Bank (ECB) and then spread to small open economies over time. The Fed introduced the first case of the QE policy in 2008 in the wake of the GFC. The ECB adopted the negative interest policy framework in 2014 to deal with the European sovereign debt crisis. Other small open economies were led to take accommodative monetary policies partly to cope with the global recession, but also to mitigate appreciation pressures on their currencies as a result of persistent monetary easing by the major central banks. For example, the central banks of Denmark, Sweden, and Switzerland explicitly stated that the motivation behind their introduction of negative policy interest rates was to deter capital inflows (BIS (2019) and SNB (2015)). The combination of this fact with the regression result suggests that the underlying mechanism for how inflation comovement has strengthened since the global financial crisis. Hit by the crisis, the major countries adopted the UMP to deal with the large deflationary shock, which was transmitted to small open economies through

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Table 5. Source of inflation comovement. The changes in portion of the two global factors before and after the break are denoted by ΔVAR_{Total}. ΔVAR_C and ΔVAR_{NC} denote the log changes in the commodity and noncommodity global factor portions, respectively. *dummy(G8)* is the dummy variable for the G8 countries. The prior distribution for the coefficients is given by $\mathcal{N}(0, 9)$, and the error variance is assumed to follow $\mathcal{IG}(5, 3)$. The posterior standard errors are in the parentheses. * indicates that 95% credibility intervals do not contain zero

	ΔVAR_{Total}			ΔVAR_{NC}			ΔVAR_C		
Dependent	$\mathcal{M}_{2G}$	$\mathcal{M}_{Euro}$	$\mathcal{M}_0$	$\mathcal{M}_{2G}$	$\mathcal{M}_{Euro}$	$\mathcal{M}_0$	$\mathcal{M}_{2G}$	$\mathcal{M}_{Euro}$	$\mathcal{M}_0$
Constant	0.32*	0.32*	0.99*	0.46*	0.46*	1.00*	0.09	0.06	0.76*
	(0.14)	(0.12)	(0.16)	(0.19)	(0.17)	(0.21)	(0.17)	(0.15)	(0.16)
					0.00				
Dummy(G8)	0.10	0.18	0.15	−0.15	−0.29	−0.21	0.42	0.65*	0.45
	(0.26)	(0.23)	(0.30)	(0.36)	(0.32)	(0.39)	(0.31)	(0.29)	(0.31)

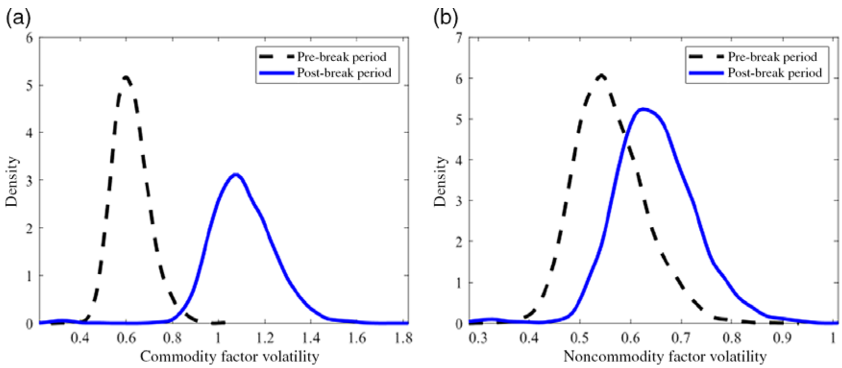

Figure 8. Factor volatilities: $\bar{\mathcal{M}}_{2G}$.

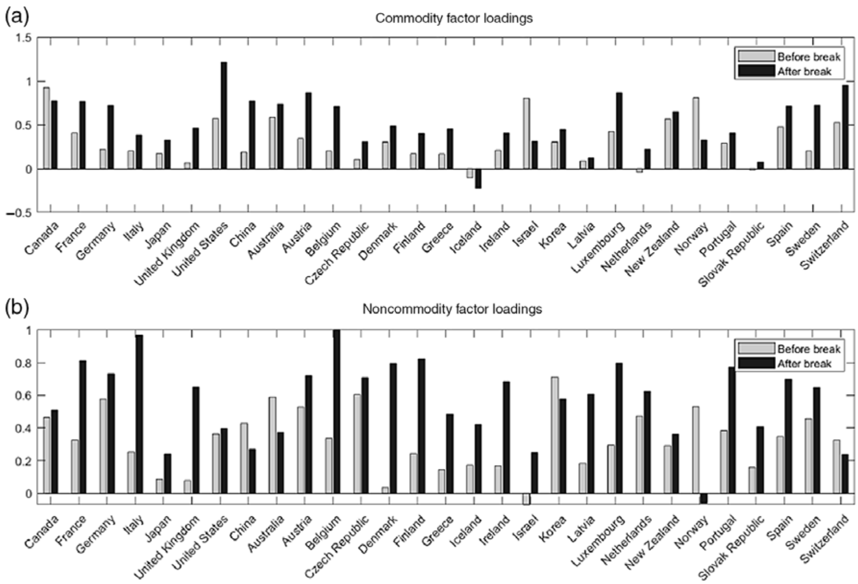

Figure 9. Factor loadings: $\mathcal{M}_{2G}$ This figure plots the posterior means of the regime-specific factor loadings across countries simulated from the model $\mathcal{M}_{2G}$.

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Table 6. The regression effects of country characteristics on the international comovement changes. *FO* is financial openness, and *UMP* is the unconventional monetary policy dummy. The log changes in the variance decomposition obtained from $\mathcal{M}_{2G}$ are used as dependent variables. The prior distribution for the coefficients is given by $\mathcal{N}(0, 9)$ and the error variance is assumed to follow $\mathcal{IG}(4, 1.5)$. * and ** indicate that the 90% and 95% posterior credibility intervals of the coefficient do not contain zero, respectively. The posterior standard errors are in the parentheses

	FO	UMP	FO×UMP
ΔVAR_{Total}	0.770	0.288	1.022
	(1.160)	(0.397)	(1.323)
ΔVAR_{C}	−0.065	−0.415	1.609
	(1.416)	(0.502)	(1.602)
ΔVAR_{NC}	1.667	1.021**	-0.053
	(1.390)	(0.491)	(1.572)
ΔVAR_{Total}	0.276		1.743**
	(0.916)		(0.858)
ΔVAR_{C}	0.594		0.594
	(1.185)		(1.115)
ΔVAR_{NC}	0.120		2.315**
	(1.209)		(1.139)
ΔVAR_{Total}	1.391**	0.512**	
	(0.654)	(0.251)	
ΔVAR_{C}	0.894	-0.051	
	(0.884)	(0.356)	
ΔVAR_{NC}	1.463*	0.981**	
	(0.836)	(0.331)	
ΔVAR_{Total}	1.520**		
	(0.731)		
ΔVAR_{C}	1.007		
	(0.918)		
ΔVAR_{NC}	1.684*		
	(0.996)		

capital flows. The interaction term of the UMP dummy and the financial openness appears to capture the economies for which the transmission of the deflationary shock was more pronounced.

Finally, this line of reasoning yields an implication on regarding the nature of the global noncommodity factor extracted by our model: it reflects the transmitted component of the deflationary shock originated in the major economies through capital flows to other economies. To test this, we examine the empirical relationship of the global noncommodity factor with the credit flows from the center, specifically the US, to the rest of the world. To be specific, we regress each global factor on the lagged global liquidity index for US dollar obtained from the BIS. The regression results are given in Table 7. We find that the global credit flows in dollars are positively related to the global noncommodity factor extracted by our model after the GFC with statistical significance, but we find no such relationship for the pre-crisis period.

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Table 7. The regression effects of global liquidity on the global factors. GL(-5) indicates the lagged global liquidity index, and the lag is five quarters. D is a time dummy variable, where it is equal to 0 before the break and 1 after the break. The global liquidity index captures the changes in the total sum of bank loans to nonbanks and debt securities issuance by nonbanks in USD. The global liquidity index can be obtained from the Bank of International Settlement. The dependent variable is the commodity factor or noncommodity factor estimated from the models $\mathcal{M}_{2G}$, $\mathcal{M}_{Euro}$, and $\mathcal{M}_0$. The prior distributions for the regression coefficients and error variance are given by $\mathcal{N}(0, 1)$ and $\mathcal{IG}(10, 5)$, respectively. The asterisk indicates that the 95% posterior credibility intervals do not contain zero

	Commodity factor			Noncommodity factor		
	Intercept	GL(-5)	D×GL(-5)	Intercept	GL(-5)	D×GL(-5)
M_{2G}	0.152	−0.054	1.066*	0.078	0.032	0.564*
	(0.096)	(0.127)	(0.194)	(0.119)	(0.155)	(0.233)
M_{Euro}	0.150	−0.052	1.063*	0.079	0.034	0.560*
	(0.096)	(0.127)	(0.191)	(0.118)	(0.157)	(0.234)
M_0	0.150	0.097	1.040*	0.073	−0.077	0.516*
	(0.084)	(0.113)	(0.167)	(0.121)	(0.162)	(0.240)

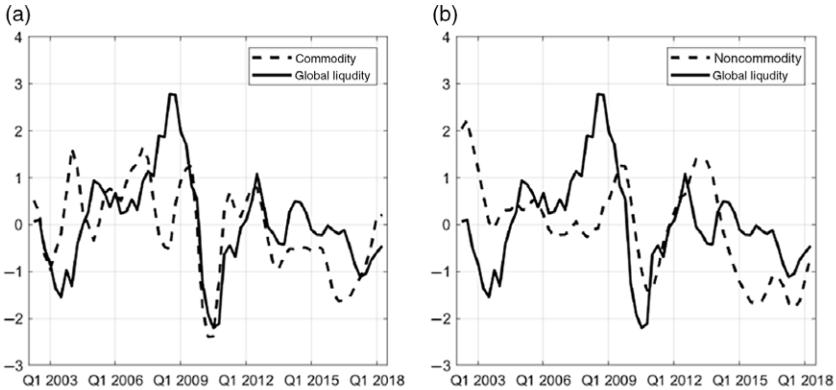

Figure 10. Global liquidity and global factors. This figure plots the global liquidity index denominated by USD along with the commodity and noncommodity factors. The global factors are estimated from the model $\mathcal{M}_{2G}$. All variables are normalized by *z*-score.

5. Summary and conclusion

In this study, we provide evidence of increased CPI global inflation synchronization after the global financial crisis. We find that the larger impact of noncommodity global factor on domestic inflation rates contributes to the overall pattern of stronger comovement. These results are robust to changes in specification. We find that the increased global synchronization is positively correlated to the increase in international financial flows, or de facto financial openness. We further find that the positive correlation is mostly driven by the economies under the UMP regime. In relation to this, we also find that the global liquidity indicator explains the inflation comovement after the GFC. As a result, for the driving force behind the higher inflation comovement, we are inclined to the interpretation that the combination of the adoption of the UMP regime by major central banks, which was induced by the large deflationary shock of the global financial crisis, and the spread of the deflationary shock and the monetary policy regime to small open economies through financial flows constitute the underlying mechanism of the global inflation synchronization in the post-GFC era.

Despite our interesting findings, a caveat is warranted. We repeated our empirical analyses for national core inflation rates and did not find strong evidence of international comovement. As Forbes (2019), Förster and Tillmann (2014), Álvarez et al. (2019), and Ha et al. (2019) document, international comovement in core inflation is much weaker than that in CPI inflation. The empirical result that the global noncommodity factor from our model significantly affects CPI but not core inflation indicates that there is a channel through which the global noncommodity factor influences noncore as well as core prices. In the presence of the channel, the effect of the global noncommodity factor on core prices may appear smaller than the one on noncore prices because it is indeed smaller. Conversely, this may be because the stabilizing role of monetary policy in response to global shocks is more effective on core prices. The source of the difference in the global comovement between the two inflation measures in the post-GFC era remains unclear; we leave this for future research.

Notes

1 In this paper, we do not consider developing countries, because we found that evidences for the global synchronization of inflation rates as well as the structural break around the GFC were less clear when developing countries were included. This is consistent with the finding of Parker (2018) that the global inflation does not explain the observed CPI inflation rates of middle- and low-income countries.
2 We identify the advanced economies from the IMF classification in the World Economy Outlook.
3 Brož and Kočenda (2018) also find a stronger inflation convergence in the European Union compared to before the crisis period.
4 For an extensive survey, see Kose et al. (2019).
5 For example, Mumtaz and Surico (2012), Kamber and Wong (2020), and Altansukh et al. (2017) document that the decline in inflation level over the 1980s and 1990s is a common phenomenon across the industrialized economies.
6 For a detailed discussion, see Gonzalez-Astudillo et al. (2016).
7 Slovak Republic (2009) and Latvia (2014) replaced their own currencies with the Euro in 2009 and 2014, respectively. From the time that elapsed since these countries joined the Euro region, we use our discretion and categorize the Slovak Republic as Euro member countries, but Latvia as non-Euro.
8 Because the likelihood cannot be analytically obtained, we rely on the Kim Filter. The detailed procedure is given in Appendix B. Recently, Kim and Kang (2019) rigorously evaluated the approximation error in the Kim filter and documented that the method gives an accurate likelihood inference compared to the particle filter method.
9 Note that N-change-point models do not have to necessarily detect N breakpoint estimates, because N indicates the maximum number of structural breaks. Less than N structural breaks may be estimated based on the available data.
10 For a robustness check, we attempt to remove deterministic trends in each time series and re-estimate the models using the detrended data. The results including the posterior distributions of the breakpoint, variance decomposition, and factor loadings for each model are provided in Appendix C. The key findings that a one-time break occurred around 2009 and that the role of global factors in explaining the national inflation rates has increased since the break and this is mainly driven by the increased effects of the noncommodity factor are robust.
11 To save the space we do not report the results.

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Appendix A. POSTERIOR SAMPLING PROCEDURE

A.1 SAMPLING FACTOR LOADINGS

This appendix discusses the details of posterior sampling algorithm for parameters, factors, and regimes, beginning with factor loadings. Let $\pi^A_{i,t}$ denote the ith element of π^A_t, and $\Gamma^A_i = (\delta^A_{i,1}, \delta^A_{i,2}, \gamma^A_{i,1}, \gamma^A_{i,2}, \kappa_{i,1}, \kappa_{i,2})'$ be its factor loadings. ψ^A_i and Σ^A_i are the ith diagonal elements of ψ^A and Σ^A, respectively. Then, the conditional distribution of $\pi^A_{i,t}$ given $(\mathbf{S}, \mathbf{B}, \mathcal{F}_{t-1}, \theta)$ is obtained as

$$
\begin{aligned}
&\pi^A_{i,t} - \psi^A_i \pi^A_{i,t-1} | \mathbf{S}, \mathbf{B}, \mathcal{F}_{t-1}, \theta \\
&\sim \begin{cases}
\mathcal{N}\left(\left[\begin{array}{cccccc} (G^C_t - \psi^A_i G^C_{t-1}) & 0 & (G^{NC}_t - \psi^A_i G^{NC}_{t-1}) & 0 & (A_t - \psi^A_i A_{t-1}) & 0 \end{array}\right] \Gamma^A_i, \Sigma^A_i\right) & \text{if } t < t^* \\
\mathcal{N}\left(\left[\begin{array}{cccccc} -\psi^A_i G^C_{t-1} & G^C_t & -\psi^A_i G^{NC}_{t-1} & G^{NC}_t & -\psi^A_i A_{t-1} & A_t \end{array}\right] \Gamma^A_i, \Sigma^A_i\right) & \text{if } t = t^* \\
\mathcal{N}\left(\left[\begin{array}{cccccc} 0 & (G^C_t - \psi^A_i G^C_{t-1}) & 0 & (G^{NC}_t - \psi^A_i G^{NC}_{t-1}) & 0 & (A_t - \psi^A_i A_{t-1}) \end{array}\right] \Gamma^A_i, \Sigma^A_i\right) & \text{if } t > t^*
\end{cases},
\end{aligned}
$$

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where t^* is the breakpoint. As the regressors are different depending on time t, the covariate matrix is given by

$$D=\begin{bmatrix} G_2^C-\psi_i^AG_1^C & 0 & G_2^{NC}-\psi_i^AG_1^{NC} & 0 & A_2-\psi_i^AA_1 & 0 \\ G_3^C-\psi_i^AG_2^C & 0 & G_3^{NC}-\psi_i^AG_2^{NC} & 0 & A_3-\psi_i^AAl2 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ G_{t^*-1}^C-\psi_i^AG_{t^*-2}^C & 0 & G_{t^*-1}^{NC}-\psi_i^AG_{t^*-2}^{NC} & 0 & A_{t^*-1}-\psi_i^AA_{t^*-2} & 0 \\ -\psi_i^AG_{t^*-1}^C & G_{t^*}^C & -\psi_i^AG_{t^*-1}^{NC} & G_{t^*} & -\psi_i^AA_{t^*-1} & A_{t^*} \\ 0 & G_{t^*+1}^C-\psi_i^AG_{t^*}^C & 0 & G_{t^*+1}^{NC}-\psi_i^AG_{t^*}^{NC} & 0 & A_{t^*+1}-\psi_i^AA_{t^*} \\ 0 & G_{t^*+2}^C-\psi_i^AG_{t^*+1}^C & 0 & G_{t^*+2}^{NC}-\psi_i^AG_{t^*+1}^{NC} & 0 & A_{t^*+2}-\psi_i^AA_{t^*+1} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & G_T^C-\psi_i^AG_{T-1}^C & 0 & G_T^{NC}-\psi_i^AG_{T-1}^{NC} & 0 & A_T-\psi_i^AA_{T-1} \end{bmatrix}.$$

If $\Pi_i^A=\{\pi_{i,t}^A-\psi_i^A\pi_{i,t-1}^A\}_{t=2}^T$ is the $(T-1)$-dimensional vector of the dependent variable, then Γ_i^A is updated by its normal full conditional distribution,

$$\Gamma_i^A|\mathbf{S},\mathbf{B},\mathcal{F}_{t-1},\theta_{-\Gamma_i^A}\sim\mathcal{N}\left(\left(\left(V_i^A\right)^{-1}+\left(\Sigma_i^A\right)^{-1}D'D\right)^{-1}\left(\left(V_i^A\right)^{-1}\bar{\Gamma}_i^A+\left(\Sigma_i^A\right)^{-1}D'\Pi_i^A\right),\left(\left(V_i^A\right)^{-1}+\left(\Sigma_i^A\right)^{-1}D'D\right)^{-1}\right),$$

given its conjugate prior, $\Gamma_i^A\sim\mathcal{N}\left(\bar{\Gamma}_i^A,V_i^A\right)$. By repeating this for all $i=1,2,..,M_A$, we sample $(\delta_{s_t}^A,\gamma_{s_t}^A,\kappa_{s_t})$. Similarly, $\delta_{s_t}^X$ and $(\delta_{s_t}^{G8},\gamma_{s_t}^{G8})$ can be simulated. This algorithm can be generalized directly to the case with more than one breakpoint.

A.2 SAMPLING (Φ,ψ,Σ)

The time series of the ith element of $\mathbf{f}_t$ over $t\in[t_0,t_1]$ is denoted by $F_{i,t_0:t_1}$. Then, the ith auto-regressive coefficient of Φ, Φ_i, whose conjugate prior is $\mathcal{N}\left(\bar{\Phi}_i,V_i^{\Phi}\right)$ is simply sampled from its full conditional distribution,

$$\Phi_i|\mathbf{S},\mathbf{B},\mathcal{F}_{t-1},\theta_{-\Phi_i}\sim\mathcal{N}\left(\left(\left(V^{\Phi}\right)^{-1}+F'_{i,1:T-1}F_{i,1:T-1}\right)^{-1}\left(\left(V^{\Phi}\right)^{-1}\bar{\Phi}+F'_{i,1:T-1}F_{i,2:T}\right),\ \left(\left(V^{\Phi}\right)^{-1}+F'_{i,1:T-1}F_{i,1:T-1}\right)^{-1}\right).$$

Similarly, each autoregressive coefficient in ψ is also simulated from its normal full conditional distribution,

$$\mathcal{N}\left(\left(\left(V^{\psi}\right)^{-1}+\sum_{t=2}^T\left(\varepsilon_{i,t-1}^A\right)^2\right)^{-1}\left(\left(V^{\psi}\right)^{-1}\bar{\psi}+\left(\sum_{t=2}^T\varepsilon_{i,t}^A\varepsilon_{i,t-1}^A\right)\right),\left(\left(V^{\psi}\right)^{-1}+\sum_{t=2}^T\left(\varepsilon_{i,t-1}^A\right)^2\right)^{-1}\right).$$

The full conditional distribution of the error variances in Σ is mutually independent inverse gamma distributions. For instance, by letting $\varepsilon_{i,t}^A$ and ψ_i^A denote the ith elements of ε_t^A and ψ^A, respectively, the ith variance in Σ^A can be drawn from

$$\mathcal{IG}\left(\left(\bar{\nu}+T-1\right)/2,\left(\bar{\delta}+\sum_{t=2}^T\left(\varepsilon_{i,t}^A-\psi_i^A\varepsilon_{i,t-1}^A\right)^2\right)/2\right).$$

A.3 SAMPLING REGIMES

We now generate regimes $\mathbf{S}$ based on the multi-move method of Chib (1998). For this, we jointly sample $\mathbf{S}$ from $\mathbf{S}|\mathbf{y},\mathbf{B},\theta$ by drawing s_t with the probability mass of $\Pr[s_t=i|\mathbf{y},\mathbf{F},s_{t+1}=j,\Theta]$ for $t=T,T-1,..,2,1$. The probability mass is computed from the Bayes rule as follows:

$$\Pr[s_t=i|\mathbf{y},\mathbf{F},s_{t+1}=j,\Theta]=\frac{\Pr[s_{t+1}=j|s_t=i]\Pr[s_t=j|\mathbf{y}_t,\mathbf{F}_{t-1},\theta]}{\sum_{i=1}^J\Pr[s_{t+1}=j|s_t=i]\Pr[s_t=j|\mathbf{y}_t,\mathbf{F}_{t-1},\theta]},$$

where

$$\begin{aligned}\Pr[s_{t-1}=i,s_t=j|\mathbf{y}_{t-1},\mathbf{F}_{t-1},\theta]&=\Pr[s_{t-1}=i|\mathbf{y}_{t-1},\mathbf{F}_{t-1},\theta]\Pr[s_t=j|s_{t-1}=i]\\&=\Pr[s_{t-1}=i|\mathbf{y}_{t-1},\mathbf{F}_{t-1},\theta]\times p_{ij},\end{aligned}$$

$$\begin{aligned}p(y_t|\mathbf{y}_{t-1},\mathbf{F}_{t-1},\theta,s_{t-1}=i,s_t=j)&=\int p(y_t,\mathbf{f}_t|\mathbf{y}_{t-1},\mathbf{F}_{t-1},\theta,s_{t-1}=i,s_t=j)d\mathbf{f}_t\\&=\int p(y_t|\mathbf{y}_{t-1},\mathbf{f}_t,\mathbf{F}_{t-1},\theta,s_{t-1}=i,s_t=j)p(\mathbf{f}_t|\mathbf{y}_{t-1},\mathbf{F}_{t-1},\theta,s_{t-1}=i,s_t=j)d\mathbf{f}_t\\&=\mathcal{N}(y_t|\psi y_{t-1}+\Gamma_j\Phi\mathbf{f}_{t-1}-\psi\Gamma_i\mathbf{f}_{t-1},\Gamma_j\Gamma_j'+\Sigma),\end{aligned}$$

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$$p(y_t|\mathbf{y}_{t-1},\mathbf{F}_{t-1},\theta)=\sum_{j=1}^{J}\sum_{i=1}^{J}p(y_t|\mathbf{y}_{t-1},\mathbf{F}_{t-1},\theta,s_{t-1}=i,s_t=j)\Pr[s_{t-1}=i,s_t=j|\mathbf{y}_{t-1},\mathbf{F}_{t-1},\theta],$$

$$\Pr[s_{t-1}=i,s_t=j|\mathbf{y}_t,\mathbf{F}_{t-1},\theta]=\frac{p(y_t|\mathbf{y}_{t-1},\mathbf{F}_{t-1},\theta,s_{t-1}=i,s_t=j)\Pr[s_{t-1}=i,s_t=j|\mathbf{y}_{t-1},\mathbf{F}_{t-1},\theta]}{p(y_t|\mathbf{y}_{t-1},\mathbf{F}_{t-1},\theta)},$$

$$\Pr[s_t=j|\mathbf{y}_t,\mathbf{F}_{t-1},\theta]=\sum_{i=1}^{J}\Pr[s_{t-1}=i,s_t=j|\mathbf{y}_t,\mathbf{F}_{t-1},\theta],$$

given the initial filtered probability mass, $\Pr[s_1=1|\mathbf{y}_1,\mathbf{F}_1,\theta]=1$.

A.4 SAMPLING F

Let $\beta_t=(\mathbf{f}_t',\varepsilon_t')'$ be the vector of the common and dependent-specific factors at time t. Then, the factor process can be expressed as

$$\beta_t|\beta_{t-1},\theta\sim N(G\beta_{t-1},\Omega),$$

where $G=diag(\Phi,\psi)$ and $\Omega=diag(I_4,\Sigma)$ are block diagonal matrices. The measurement equation can be rewritten as

$$y_t \;=\; \underbrace{(\Gamma_{s_t},I_{9+M_A})}_{\Lambda_{s_t}} \;\times\; \beta_t.$$

Given the state-space representation, we apply Carter and Kohn (1994)'s Gibbs-sampling method for factor sampling. This method consists of two stages. The first is Kalman filtering, which provides the Gaussian filtered distribution of the factors as

$$\begin{aligned}
\mathbb{E}(\beta_t|\mathbf{y}_{t-1},\mathbf{S},\theta)&=\beta_{t|t-1}=G\beta_{t-1|t-1},\\
Var(\beta_t|\mathbf{y}_{t-1},\mathbf{S},\theta)&=V_{t|t-1}=GP_{t-1|t-1}G'+\Omega,\\
\mathbb{E}(y_t|\mathbf{y}_{t-1},\mathbf{S},\theta)&=y_{t|t-1}=\Lambda_{s_t}\beta_{t|t-1},\\
Var(y_t|\mathbf{y}_{t-1},\mathbf{S},\theta)&=k_{t|t-1}=\Lambda_{s_t}V_{t|t-1}\Lambda_{s_t}',\\
\beta_{t|t}&=\beta_{t|t-1}+V_{t|t-1}\Lambda_{s_t}'k_{t|t-1}^{-1}(y_t-y_{t|t-1}),\\
V_{t|t}&=V_{t|t-1}-V_{t|t-1}\Lambda_{s_t}'k_{t|t-1}^{-1}\Lambda_{s_t}V_{t|t-1}.
\end{aligned}$$

In the second stage, β_t is sampled from the conditional distribution

$$\beta_t|\beta_{t+1},\mathbf{y}_t,\mathbf{S},\theta\sim\mathcal{N}\left(\beta_{t|t,\beta_{t+1}},V_{t|t,\beta_{t+1}}\right),$$

in a backward recursion. By the Bayes rule, the conditional mean and variance are computed as

$$\begin{aligned}
\beta_{t|t,\beta_{t+1}}&=\beta_{t|t}+V_{t|t}G'V_{t+1|t}^{-1}(\beta_{t+1}-\beta_{t+1|t}),\\
\text{and } V_{t|t,\beta_{t+1}}&=V_{t|t}-V_{t|t}G'V_{t+1|t}^{-1}GV_{t|t},
\end{aligned}$$

respectively, where $\beta_{t+1|t}=G\beta_{t|t}$ and $V_{t+1|t}=GV_{t|t}G'+\Omega$. Once β_T is drawn from its filtered distribution, $\mathcal{N}\left(\beta_{T|T},V_{T|T}\right)$, then β_t is sampled from $\mathcal{N}\left(\beta_{t|t,\beta_{t+1}},V_{t|t,\beta_{t+1}}\right)$ for $t=T-1,T-2,..,1$. The first five elements of β_t are retained as the posterior draws for the common factors. Note that the prior distribution of β_0 is the unconditional factor distribution, $\mathcal{N}(0,\bar{V}_{\beta_0}=(I_{9+4+M_A}-G^2)^{-1}\Omega)$. As $\beta_1|\beta_0,\theta\sim\mathcal{N}\left(G\beta_0,\Omega\right)$, β_0 is updated as

$$\beta_0|\beta_1,\theta\sim\mathcal{N}\left((\bar{V}_{\beta_0}^{-1}+G'\Omega^{-1}G)^{-1}G'\Omega^{-1}\beta_1,(\bar{V}_{\beta_0}^{-1}+G'\Omega^{-1}G)^{-1}\right),$$

given its prior and β_1.

A.5 SAMPLING TRANSITION PROBABILITIES

Finally, the transition probabilities are sampled conditional on the regimes and their conjugate beta priors. Let the total number of one-step transitions from regime j to regime j be denoted by n_j. Then, the full conditional distribution of p_{jj} for $j=1,2,..,J-1$ is analytically derived as a beta distribution,

$$p_{jj}\sim beta(a_{j,j}+n_j,a_{j,j+1}+1). \tag{A1}$$

Appendix B. Likelihood

We test the statistical significance of structural breaks by the Bayes factor, which is the ratio of the marginal likelihood of the models with different number of structural breaks. The log marginal likelihood of model $\mathcal{M}$, denoted by $p(\mathbf{y}|M)$, can be computed on the identity,

$$\log p(\mathbf{y}|\mathcal{M}) = \log p(\mathbf{y}|\hat{\theta}, \mathcal{M}) + \log \pi(\hat{\theta}|\mathcal{M}) - \log \pi(\hat{\theta}|\mathbf{y},\mathcal{M}),$$

where $p(\mathbf{y}|\hat{\theta}, \mathcal{M})$ is the likelihood, $\pi(\hat{\theta}|\mathcal{M})$ is the prior density, and $\pi(\hat{\theta}|\mathbf{y},\mathcal{M})$ is the posterior density of the parameters at $\hat{\theta}$. $\hat{\theta}$ is typically chosen at the posterior mode. The prior density is immediately calculated, given the mutually independent prior distributions. The posterior density is obtained by the Chib's method (Chib (1995)) using the Gibbs-sampling outputs. Finally, we rely on the Kim filter (KF) of Kim (1994) to compute the likelihood as it is not analytically obtained. Here, we briefly describe the KF algorithm. The KF method consists of three steps. Let $\beta^{(i)}_{t-1|t-1} = \mathbb{E}[\beta_t|\mathcal{F}_{t-1}, \theta, s_{t-1} = i]$ and $P^{(i)}_{t-1|t-1} = Var[\beta_t|\mathcal{F}_{t-1}, \theta, s_{t-1} = i]$ denote the conditional expectation and variance-covariance of β_t, given $(\mathcal{F}_{t-1}, \theta, s_{t-1} = i)$, respectively. Then, the first step is to run the conditional Kalman filter, given $(s_{t-1} = i, s_t = j)$, which provides the conditional expectation and variance-covariance of the unobserved components and observations as follows:

$$\begin{aligned}
\mathbb{E}[\beta_t|\mathcal{F}_{t-1}, \theta, s_t = j, s_{t-1} = i] &= \beta^{(i,j)}_{t|t-1} = G\beta^{(i)}_{t-1|t-1},\\
Var[\beta_t|\mathcal{F}_{t-1}, \theta, s_t = j, s_{t-1} = i] &= P^{(i,j)}_{t|t-1} = GP^{(i)}_{t-1|t-1}G' + \Omega,\\
\mathbb{E}[y_t|\mathcal{F}_{t-1}, \theta, s_t = j, s_{t-1} = i] &= y^{(i,j)}_{t|t-1} = y_t - \Lambda_j\beta^{(i,j)}_{t|t-1},\\
Var[y_t|\mathcal{F}_{t-1}, \theta, s_t = j, s_{t-1} = i] &= f^{(i,j)}_{t|t-1} = \Lambda_j P^{(i,j)}_{t|t-1}\Lambda_j',\\
\mathbb{E}[\beta_t|\mathcal{F}_t, \theta, s_t = j, s_{t-1} = i] &= \beta^{(i,j)}_{t|t} = \beta^{(i,j)}_{t|t-1} + K^{(i,j)}_t(y_t - y^{(i,j)}_{t|t-1}),\\
Var[\beta_t|\mathcal{F}_t, \theta, s_t = j, s_{t-1} = i] &= P^{(i,j)}_{t|t} = P^{(i,j)}_{t|t-1} - K^{(i,j)}_t\Lambda_j P^{(i,j)}_{t|t-1},
\end{aligned}$$

where $K^{(i,j)}_t = P^{(i,j)}_{t|t-1}\Lambda_j(f^{(i,j)}_{t|t-1})^{-1}$ is the Kalman gain conditioned on $s_t = j$ and $s_{t-1} = i$ for $i, j = 1, 2, \ldots, N$. In the second step, we apply the Hamilton filter of Hamilton (1989), and obtain the likelihood density, $p(y_t|\mathcal{F}_{t-1}, \theta)$ and the filtered probabilities. Given the filtered probability at time $t-1$, $\texttt{Pr}(s_{t-1}|\mathcal{F}_{t-1}, \theta)$, the predictive joint density of the regimes is obtained as

$$\texttt{Pr}(s_t, s_{t-1}|\mathcal{F}_{t-1}, \theta) = \texttt{Pr}[s_t|s_{t-1}]p(s_{t-1}|\mathcal{F}_{t-1}, \theta).$$

Then, the likelihood density can be obtained by integrating the conditional density of the observation, $p(y_t|\mathcal{F}_{t-1}, \theta, s_t, s_{t-1})$, over the regimes,

$$p(y_t|\mathcal{F}_{t-1}, \theta) = \sum\nolimits_{s_t}\sum\nolimits_{s_{t-1}} p(y_t|\mathcal{F}_{t-1}, \theta, s_t, s_{t-1})\texttt{Pr}(s_t, s_{t-1}|\mathcal{F}_{t-1}, \theta).$$

The conditional distribution of y_t is normal, given $(\mathcal{F}_{t-1}, \theta, s_t = j, s_{t-1} = i)$, and so we have

$$p(y_t|\mathcal{F}_{t-1}, \theta, s_t = j, s_{t-1} = i) = \mathcal{N}\left(y_t|y^{(i,j)}_{t|t-1}, f^{(i,j)}_{t|t-1}\right).$$

The filtered probabilities, $\texttt{Pr}(s_t|\mathcal{F}_t, \theta)$, are simply updated by the Bayes rule as follows:

$$\texttt{Pr}(s_t|\mathcal{F}_t, \theta) = \sum\nolimits_{s_{t-1}} \frac{p(y_t|\mathcal{F}_{t-1}, \theta, s_t, s_{t-1})\texttt{Pr}(s_t, s_{t-1}|\mathcal{F}_{t-1}, \theta)}{p(y_t|\mathcal{F}_{t-1}, \theta)}.$$

The final step, referred to as approximation, is to derive the filtered distribution of β_t,

$$\beta_t|\mathcal{F}_t, \theta, s_t.$$

Given the normality assumption and filtered probabilities, $\beta^j_{t|t} = \mathbb{E}[\beta_t|\mathcal{F}_t, \Theta, \mathbf{P}, s_t = j]$ and $P^j_{t|t} = Var[\beta_t|\mathcal{F}_t, \Theta, \mathbf{P}, s_t = j]$ are approximated by the mixture of N regimes such that

$$\begin{aligned}
\beta^j_{t|t} &= \frac{\sum_{i=1}^N \texttt{Pr}(s_t = j, s_{t-1} = i|\mathcal{F}_t, \theta v)\beta^{(i,j)}_{t|t}}{\texttt{Pr}(s_t = j|\mathcal{F}_t, \theta)}, \text{ and}\\
P^j_{t|t} &= \frac{\sum_{i=1}^N \texttt{Pr}(s_t = j, s_{t-1} = i|\mathcal{F}_t, \theta)[P^{(i,j)}_{t|t} + (\beta^j_{t|t} - \beta^{(i,j)}_{t|t})(\beta^j_{t|t} - \beta^{(i,j)}_{t|t})']}{\texttt{Pr}(s_t = j|\mathcal{F}_t, \theta)}.
\end{aligned} \tag{B1}$$

By repeating these three steps at every time point sequentially at $\theta = \hat{\theta}$, we can complete the log likelihood calculation,

$$\log p(\mathbf{y}|\hat{\theta}, \mathcal{M}) = \sum\nolimits_{t=1}^T p(y_t|\mathcal{F}_{t-1}, \hat{\theta}).$$

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Appendix C. DETRENDED DATA RESULTS

This section reports the variance decomposition results for the linearly detrended data. Tables C.1, C.2, and C.3 present the posterior means of the variance decomposition from the models $\mathcal{M}_{2G}$, $\mathcal{M}_{Euro}$, and $\mathcal{M}_0$, respectively. Figures C.1, C.2, and C.3 provide the posterior means and 90% credibility intervals of the commodity and noncommodity factor shares. Finally, Figure C.4 displays the posterior probabilities of the changepoints across the models.

Table C.1. Variance decomposition of linearly detrended CPI inflation rates and commodity price: $\mathcal{M}_{2G}$. This table presents the posterior estimates of the variance decomposition of each country's linearly detrended inflation in percentage before and after the break based on 5000 posterior draws

	Global									
	Commodity		Non -commodity		G8 country		Advanced country		Country -specific	
Factor	($G^C{}_t$)		($G^{NC}{}_t$)		($G8_t$)		(A_t)		(ε_t)	
Regime	1	2	1	2	1	2	1	2	1	2
Commodity price	54.5	88.7	0.0	0.0	0.0	0.0	0.0	0.0	45.5	11.3
(a) G8 countries										
Canada	58.1	33.2	5.6	16.8	8.4	20.6	0.0	0.0	27.9	29.4
France	32.8	43.8	18.1	48.1	12.2	2.4	0.0	0.0	36.9	5.6
Germany	9.6	37.7	50.6	43.8	12.3	2.0	0.0	0.0	27.5	16.6
Italy	36.7	12.2	17.4	83.8	6.4	0.6	0.0	0.0	39.6	3.4
Japan	22.7	7.4	14.4	8.0	9.3	76.4	0.0	0.0	53.6	8.2
United Kingdom	5.2	15.7	5.7	46.9	5.2	6.3	0.0	0.0	83.9	31.1
United States	54.5	72.3	19.9	11.5	3.1	6.7	0.0	0.0	22.6	9.5
China	5.8	55.5	45.7	10.9	8.9	1.9	0.0	0.0	39.6	31.7
(b) Advanced countries										
Australia	34.0	38.5	13.8	9.0	0.0	0.0	12.6	20.2	39.5	32.3
Austria	12.4	42.7	38.3	37.7	0.0	0.0	11.1	3.7	38.3	15.9
Belgium	7.8	26.5	27.8	51.3	0.0	0.0	3.4	11.7	61.0	10.4
Czech Republic	4.6	12.8	57.7	51.1	0.0	0.0	3.0	5.4	34.7	30.6
Denmark	27.5	20.7	19.4	58.0	0.0	0.0	3.8	7.0	49.3	14.2
Finland	14.7	13.0	11.7	54.2	0.0	0.0	8.2	17.3	65.4	15.5
Greece	11.5	42.8	5.5	22.4	0.0	0.0	5.3	2.3	77.8	32.4
Iceland	7.9	8.7	10.2	19.5	0.0	0.0	2.7	37.7	79.3	34.1
Ireland	11.8	23.5	6.4	39.9	0.0	0.0	5.0	6.1	76.8	30.5
Israel	26.7	8.5	17.5	10.4	0.0	0.0	11.9	16.5	44.0	64.6
Korea	14.1	13.6	50.3	34.3	0.0	0.0	3.8	31.3	31.8	20.8
Latvia	4.6	3.8	21.8	42.4	0.0	0.0	3.1	27.1	70.5	26.8
Luxembourg	55.9	50.7	22.1	44.4	0.0	0.0	2.5	0.7	19.5	4.2
Netherlands	5.4	5.0	15.5	50.3	0.0	0.0	18.8	4.5	60.3	40.1
New Zealand	29.1	23.3	7.9	13.5	0.0	0.0	11.0	36.5	52.1	26.7
Norway	54.4	9.5	8.4	2.8	0.0	0.0	2.8	46.9	34.4	40.8
Portugal	30.3	21.8	11.6	55.9	0.0	0.0	6.3	2.9	51.7	19.4
Slovak Republic	5.4	3.6	18.4	59.8	0.0	0.0	63.2	5.3	13.0	31.4
Spain	54.2	48.0	13.9	42.1	0.0	0.0	3.0	1.0	28.9	8.8
Sweden	11.0	32.4	12.2	31.8	0.0	0.0	4.5	17.2	72.2	18.5
Switzerland	52.5	60.0	18.0	3.0	0.0	0.0	1.8	28.1	27.6	9.0

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Table C.2. Variance decomposition of linearly detrended CPI inflation rates and commodity price: $\mathcal{M}_{Euro}$ This table presents the posterior estimates of the variance decomposition of each country's linearly detrended inflation in percentage before and after the break based on 5000 posterior draws

	Global							
			Non		EU		Country	
	Commodity		-commodity		country		-specific	
Factor	($G_t{}^C$)		($G_t{}^{NC}$)		(E_t)		(ε_t)	
Regime	1	2	1	2	1	2	1	2
Commodity price	34.5	80.3	0.0	0.0	0.0	0.0	65.5	19.7
(a) G8 countries								
Canada	59.7	31.9	12.0	29.5	0.0	0.0	28.3	38.6
France	15.6	44.5	13.0	31.0	9.0	13.3	62.4	11.3
Germany	6.4	35.7	46.6	24.5	6.6	17.4	40.4	22.4
Italy	17.0	13.2	15.6	48.3	9.6	27.7	57.9	10.8
Japan	7.2	12.8	9.4	33.0	0.0	0.0	83.4	54.2
United Kingdom	7.1	10.9	8.3	59.3	0.0	0.0	84.6	29.8
United States	36.9	68.6	23.5	13.9	0.0	0.0	39.6	17.5
China	4.5	52.1	39.3	11.1	0.0	0.0	56.1	36.8
(b) Advanced small countries								
Australia	35.3	36.6	23.2	21.9	0.0	0.0	41.5	41.5
Austria	10.0	40.5	35.2	30.9	11.2	9.2	43.7	19.5
Belgium	5.0	24.6	22.5	50.0	3.8	8.9	68.6	16.4
Czech Republic	5.3	18.6	43.9	39.4	0.0	0.0	50.8	42.0
Denmark	26.5	22.3	11.1	50.9	0.0	0.0	62.4	26.8
Finland	16.8	12.3	13.7	60.4	4.1	5.2	65.4	22.0
Greece	9.8	35.1	5.9	10.7	3.3	13.2	81.1	40.9
Iceland	8.1	8.3	8.7	42.7	0.0	0.0	83.2	49.0
Ireland	16.4	19.6	6.5	31.1	3.1	13.8	74.1	35.5
Israel	32.9	9.3	19.4	18.0	0.0	0.0	47.7	72.8
Korea	11.2	12.9	55.1	59.9	0.0	0.0	33.7	27.2
Latvia	4.4	5.6	11.2	57.6	0.0	0.0	84.4	36.8
Luxembourg	33.1	45.9	21.9	22.0	3.0	20.5	41.9	11.6
Netherlands	4.7	3.5	14.8	31.5	17.4	17.9	63.0	47.2
New Zealand	29.6	21.9	10.3	40.4	0.0	0.0	60.1	37.7
Norway	44.4	9.6	15.3	15.4	0.0	0.0	40.3	74.9
Portugal	28.9	19.3	16.1	24.5	3.1	29.2	51.9	27.0
Slovak Republic	4.2	3.4	17.4	35.6	62.6	14.6	15.8	46.4
Spain	41.5	42.2	16.8	20.3	3.0	24.6	38.7	12.9
Sweden	11.9	30.5	11.8	44.9	0.0	0.0	76.3	24.6
Switzerland	29.1	61.7	14.3	15.7	0.0	0.0	56.6	22.6

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Table C.3. Variance decomposition of linearly detrended CPI inflation rates and commodity price: $\mathcal{M}_0$. This table presents the posterior estimates of the variance decomposition of each country's linearly detrended inflation in percentage before and after the break based on 5000 posterior draws

Factor	Global Commodity ($G_t{}^C$)		Global Non -commodity ($G_t{}^{NC}$)		Country -specific (ε_t)	
Regime	1	2	1	2	1	2
Commodity price	7.9	82.7	0.0	0.0	92.1	17.3
(a) G8 countries						
Canada	22.8	47.0	24.8	22.3	52.3	30.7
France	11.8	49.9	11.7	42.8	76.5	7.3
Germany	27.4	48.0	26.7	37.6	45.9	14.4
Italy	10.8	20.1	12.7	69.9	76.5	10.0
Japan	2.3	16.0	2.8	17.4	94.9	66.6
United Kingdom	3.3	17.9	3.9	44.8	92.8	37.3
United States	23.5	77.1	23.3	11.8	53.2	11.1
China	12.4	57.1	14.9	9.4	72.7	33.6
(b) Advanced countries						
Australia	26.1	49.3	27.1	21.4	46.8	29.3
Austria	24.3	52.3	24.0	34.7	51.7	13.0
Belgium	9.0	31.7	10.0	54.6	81.1	13.8
Czech Republic	21.6	21.0	22.4	53.6	56.0	25.4
Denmark	13.6	25.2	19.5	58.1	66.9	16.7
Finland	6.4	20.0	8.4	61.0	85.2	19.0
Greece	2.2	33.6	2.7	17.7	95.1	48.7
Iceland	4.5	7.3	4.7	43.2	90.8	49.4
Ireland	6.2	26.5	9.3	39.6	84.4	33.9
Israel	14.7	11.9	19.4	21.2	65.9	66.9
Korea	23.5	19.1	21.0	52.1	55.6	28.7
Latvia	3.1	8.4	4.2	56.2	92.7	35.4
Luxembourg	24.3	55.5	24.2	38.5	51.4	6.0
Netherlands	8.8	7.3	10.2	46.6	81.0	46.1
New Zealand	12.5	31.0	15.5	34.3	72.0	34.8
Norway	14.3	11.3	17.4	8.8	68.3	80.0
Portugal	17.6	27.2	20.7	48.4	61.7	24.4
Slovak Republic	5.7	6.6	6.8	26.6	87.5	66.9
Spain	22.1	50.3	23.5	38.8	54.4	10.8
Sweden	6.1	39.4	9.1	39.3	84.8	21.3
Switzerland	10.4	63.2	11.6	11.4	78.1	25.4

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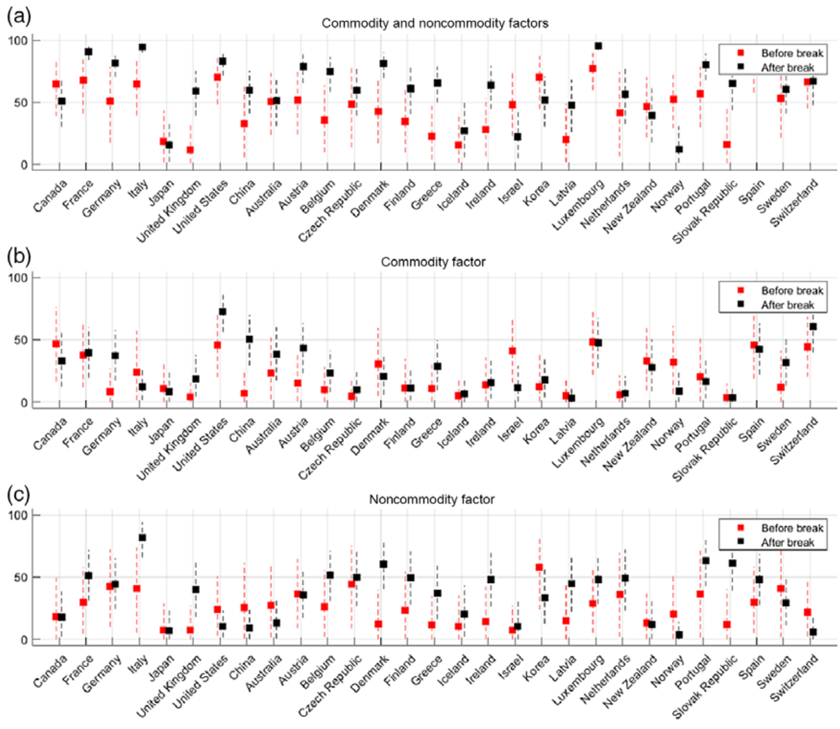

Figure C.1. Variance decomposition: $\mathcal{M}_{2G}$ and detrended data The dashed lines indicate 90% posterior credibility intervals. The red and black markers are the posterior means before and after the break, respectively.

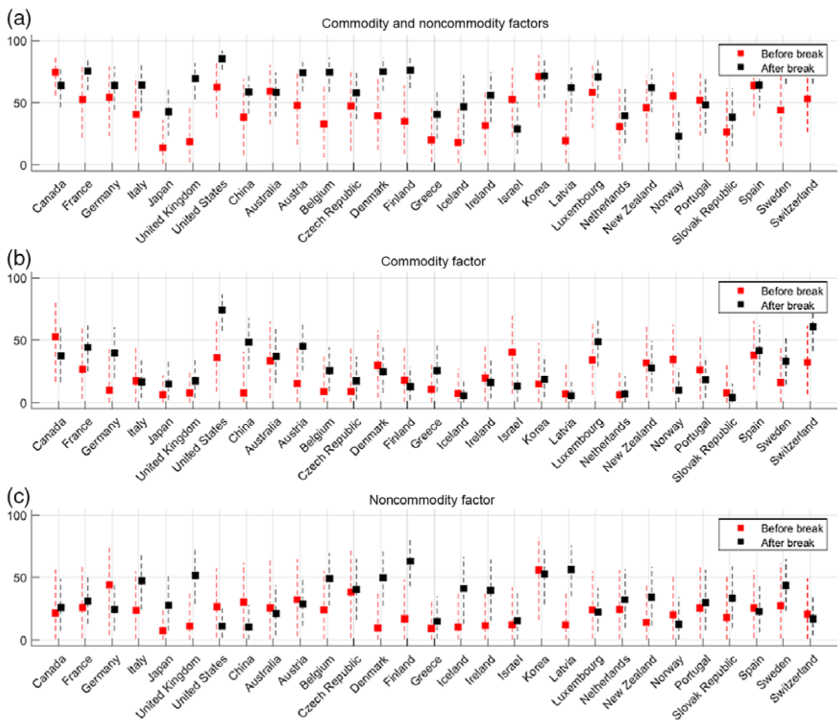

Figure C.2. Variance decomposition: $\mathcal{M}_{Euro}$ and detrended data The dashed lines indicate 90% posterior credibility intervals. The red and black markers are the posterior means using the data before and after the break, respectively.

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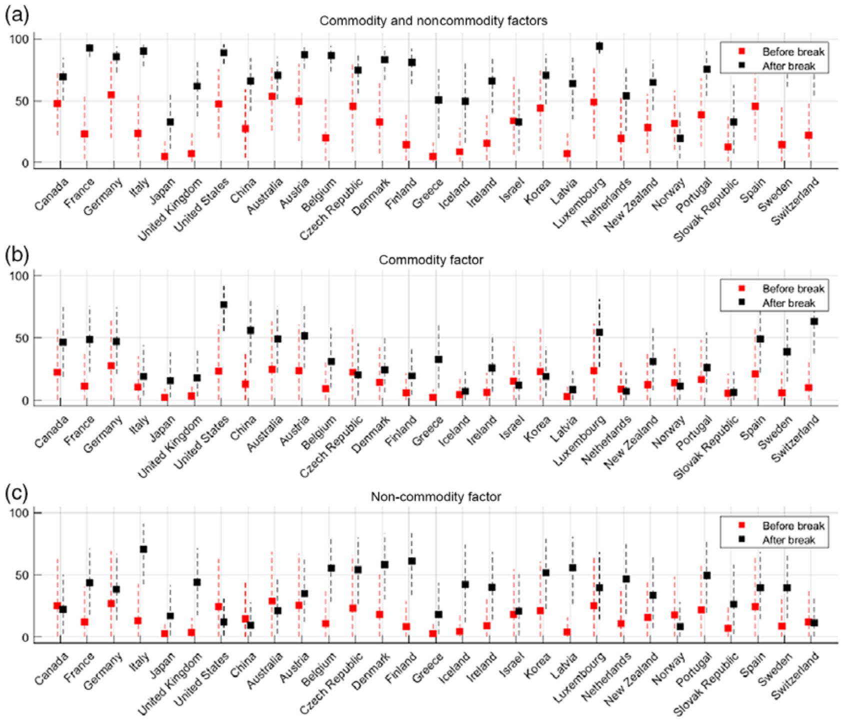

Figure C.3. Variance decomposition: $\mathcal{M}_0$ and detrended data The dashed lines indicate 90% posterior credibility intervals. The red and black markers are the posterior means using the data before and after the break, respectively.

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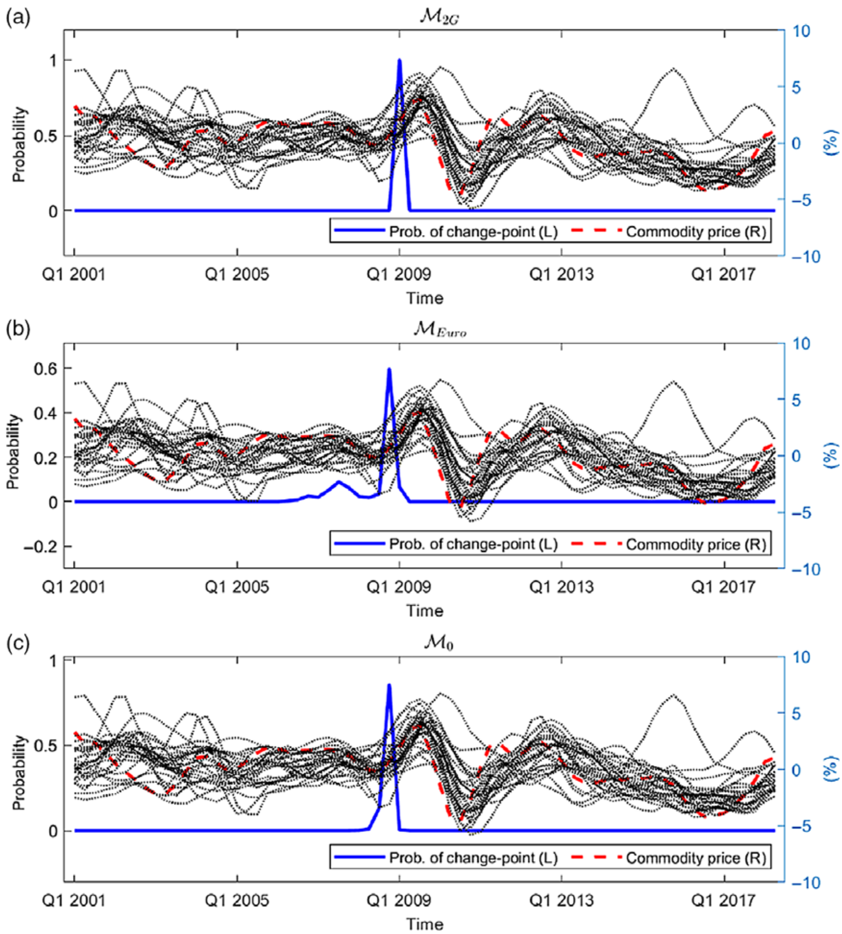

Figure C.4. Posterior probabilities of breakpoint: detrended data. This figure plots the posterior probabilities of the breakpoint across three dynamic common factor models. The dashed line is the global commodity price index growth, and the dotted lines in panels (a), (b), and (c) are the cross-country inflation rates. All observations are linearly detrended.

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