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Core Inflation in the Advanced Economies: A Regional Perspective*

Daniel O. Beltran† Julio L. Ortiz‡

Abstract

We explore differences in the dynamics of core inflation between Europe and North America using a Bayesian time series filter that decomposes the level of core inflation in the major advanced economies into regional, global, and country-specific components. We find a prominent role for both regional and global factors. Historically, the two regional components have at times diverged. Using reduced-form regressions, we examine the economic drivers behind the changes in our estimated global and regional components of U.S. core inflation, focusing on the post-pandemic inflation surge and subsequent pullback. The global component is associated with global supply frictions and past energy shocks. The North American regional component is associated with labor market tightness in the region.

Key Words: Regional inflation. Dynamic Linear Model. Core inflation.

JEL Classification: C11, C32, C53, E31, F00

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1 Introduction

Inflation dynamics sometimes exhibit striking regional patterns that cannot be fully explained by either purely domestic or purely global factors. For example, amid the oil shocks of the 1970s, cross-country inflation experiences varied in part due to oil import dependence which tended to be regional in nature. More recently, energy shocks triggered by geopolitical tensions generated disproportionately large inflationary surges in Europe compared to other regions of the world.

Intuitively, inflation could be regional in nature for a couple of reasons. First, countries within a region may share a common *exposure* to global shocks. This exposure could be shaped by a variety of factors such as the degree to which product, labor, and energy markets are regionally integrated, similar economic policies such as wage indexation, and regional similarities in consumers' preferences. Second, countries within a region may share a common *response* to global shocks. For example, countries within a region may adopt similar fiscal and monetary policies to mitigate the effects of an adverse shock. Finally, countries within the same region may face an exogenous regional shock.

In this paper, we decompose core inflation across 12 countries into regional, global, and country-specific components with a focus on Europe and North America. We find that regional inflation plays an important role in shaping inflation dynamics. In addition, we document differences in regional inflation experiences between Europe and North America. Moreover, we find that the global component of core inflation also explains a sizable share of the variation in core inflation rates and we estimate that, at present, the global component is elevated relative to recent history. Finally, in an exploratory exercise, we find that during the post-COVID inflation surge, global inflation is largely associated with supply frictions and past oil price fluctuations whereas regional inflation is largely associated with labor market tightness and consumer spending patterns.

Accounting for the presence of a regional component to inflation is important for a number of reasons. First, extracting a regional component of inflation matters for our understanding of global and domestic components, whose importance could be overstated if we were to ignore regional inflation. Second, the presence of a regional component matters for our understanding of the drivers of inflation, which could in turn have monetary policy implications. Third, the existence of regional components of inflation raises the possibility that regional-level information could potentially be useful when forecasting inflation. Obtaining a deeper understanding of regional inflation could be particularly important if the world grows increasingly fragmented (Airaudo et al., 2025; Fernández-Villaverde et al., 2024).

We start by developing a parsimonious multivariate Bayesian time series filter that is tailored to compare the inflation dynamics between Europe and North America. Our model decomposes the level of core inflation in the major advanced economies into regional, global, and country-specific components. More specifically, we assume that core inflation consists of a global and regional level factors which follow random walks with time-varying growth rates, while persistent country-specific factors follow a moving average representation.

We estimate the model parameters via maximum likelihood estimation (MLE). Our dynamic linear model (DLM) is estimated using monthly core inflation rates for 12 advanced economies going back to the 1970s. Filtering these rich monthly time series through our Bayesian state-space filter enables us to estimate the posterior means and variances of the time-varying components at each point in time.

With the estimated model in hand, we analyze each inflation component, with a focus on the global and regional components. We identify a prominent role for regional factors, consistent with Mumtaz et al. (2011) who find that regional factors account for the bulk of fluctuations in inflation and output for most countries in their sample. The European regional component tended to be higher than the North America component into the 1990s. From the late 1990s until the start of the COVID pandemic, the two regional components behaved similarly. Amid the COVID inflation surge, however, North America regional inflation peaked earlier and at a higher level than the European regional component. Both regional components have largely retraced their post-pandemic increases.

Next, we analyze the extent to which national core inflation rates are explained by the global component that is common to all countries in our sample. Our estimated global component explains a sizable fraction of core inflation in the major advanced economies, consistent with Cascaldi-Garcia et al. (2024) who estimate a global component using a dynamic factor model. The inclusion of regional components in our model affects the dynamics of the estimated global component.

Finally, we conduct an exploratory exercise in which we identify the main correlates of global and regional core inflation amid the post-COVID inflation surge. We perform a model selection exercise that considers an extensive set of possible explanatory variables. We adopt a general-to-specific model selection strategy to arrive at a parsimonious linear model. Our results suggest that the global component of core inflation is well-described by supply frictions and past fluctuations in oil prices while the regional component of core inflation is well-described by labor market tightness and consumer spending patterns.

Overall, our analysis indicates that regional inflation has played an important role in shaping inflation dynamics over the last several decades. Moreover, our exploratory exercise suggests that in recent years, global and regional inflation have moved in different directions and appear to have different drivers.

Related literature. Our paper contributes to the literature that studies global inflation. While a longstanding literature has analyzed the degree to which inflation is global in nature (Ciccarelli and Mojon, 2010; Mumtaz and Surico, 2012; Monacelli and Sala, 2009), fewer have studied its regional features. One notable study that includes a regional perspective is Mumtaz et al. (2011) which finds that regional factors account for the bulk of the fluctuations in both inflation and output growth in most countries.

On the other hand, Förster and Tillmann (2014) find that inflation is a local phenomenon. Moreover, while Parker (2018) finds that a global factor can explain much of the variation in national inflation rates among advanced economies, this finding does not extend to middle- and low-income countries. Furthermore, when examining inflation subcomponents, the authors find that the common factor of inflation only explains the variation in the energy subcomponent. Their answer to "How global is 'global' inflation?" is "Not very."

More generally, our paper relates to a broader literature that decomposes inflation into common and idiosyncratic components. Some of this literature leverages rich cross-sectional variation across subcomponents of aggregate inflation, to extract trends in U.S. inflation using dynamic factor models (Stock and Watson, 2016; Ahn and Luciani, 2024). Along these lines, in a recent study of global and idiosyncratic inflation, Cascaldi-Garcia et al. (2024) uses a dynamic factor model to estimate common global components of core, noncore, and headline inflation across 26 advanced and emerging market economies. They find that the global component accounted for a large part of the surge in core inflation in the two periods when world core inflation was high and volatile: between 1960 and the mid-1990s, and since the COVID-19 pandemic. We model country, regional, and global components with a DLM rather than a dynamic factor model. Our baseline DLM nests a simpler DLM with just a common global component and country-specific components. The estimated global component from this simpler DLM is nearly identical to that of Cascaldi-Garcia et al. (2024). We find that our baseline DLM with regional factors is favored by the data based on the log-likelihood.

We regard a Bayesian DLM as well-suited for our purposes for a few reasons. First, the parsimonious structure of our DLM model offers easily interpretable global, regional, and country-specific components whose posterior means and variances can be estimated directly using the Kalman filter. The Bayesian approach with conjugate priors greatly facilitates recursive estimation of the posterior densities. Another advantage of the DLM approach is that it readily produces the means and variances of the predictive distributions of both the observables and the states, which can be used to forecast future states and observations.

Our paper also relates to the time series literature that models inflation dynamics. Stock and Watson (2007) find that U.S. CPI inflation is well described by an integrated moving average process of order 1, which is equivalent to an unobserved components model in which inflation has a stochastic trend that follows a random walk. We adopt a similar time-series specification but in a multivariate setting, and include both a stochastic global trend that is common to all the countries in the sample as well as a stochastic regional trend that is common to just countries in the same region. The results from our approach, which uses higher-frequency (monthly) aggregate inflation measures, corroborate those of the earlier studies that have found a prominent role for regional and global components of inflation.

The rest of the paper proceeds as follows. In Section 2 we describe our data and the model used to illustrate our approach. Section 3 presents our model estimates of the global, regional, and country-specific components. Section 4 identifies the economic drivers of the global and regional components. Section 5 concludes with a discussion of implications for monetary policy.

2 Data and Model Specification

This section describes the inflation data that we feed into our Bayesian filter to derive the unobserved regional, global, and country-specific components for each country. We then specify the model used for the decomposition.

We exclude emerging market economies from our data sample for consistency and ease of interpretation of our results. That is, we intentionally restrict our sample to a set of advanced economies that follow similar inflation dynamics that are well described by a moving average representation similar to the one in Stock and Watson (2007), but in a multivariate setting with common stochastic trends.

2.1 Data

The inflation data used for our decomposition are the 12-month percent changes in the national core consumer price indexes for 12 advanced economies: Germany, Italy, France, Portugal, Netherlands, Luxembourg, Finland, Austria, United Kingdom, United States, Canada, and Japan. The core consumer price indexes are from the OECD Main Economic Indicators database.[1] The monthly data are sourced from Haver Analytics, and the sample period is January 1971 to July 2025.

2.2 Dynamic Linear Model

As shown in equation 1, we decompose each country's core inflation series, Y_{it}, into a common time-varying global level factor, μ_t^{Global}, a time-varying regional level factor (one for Europe, μ_t^{Europe}, and one for North America, $\mu_t^{\text{NorthAmerica}}$), and a persistent country-specific component that follows a moving average representation. The global and regional factors, defined in equations 2 and 4, are random walks with time-varying growth rates, β_t^{Global}

[1]We choose to use core consumer prices rather than headline consumer prices in part because the global component obtained from a decomposition of headline inflation would likely reflect energy and other commodity price fluctuations. By instead focusing on core inflation, which is often regarded as a strong signal for future headline inflation, our results could have more direct monetary policy implications. In particular, to the extent that energy and other commodity prices are important determinants of any of our estimated components, it is due to the *passthrough* of these prices to core consumer prices.

and $\beta_t^{\text{Regional}}$ (one for Europe, β_t^{Europe}, and another one for North America $\beta_t^{\text{N.Amer.}}$). These growth rates, in turn, are modeled as first-order auto-regressive processes with respective decay parameters ρ_{Global}, ρ_{Europe} and $\rho_{\text{N.Amer.}}$ (equations 3 and 5). The 9 European countries are assumed to share a time-varying European level component. The United States and Canada share a common time-varying North America component. Japan does not share a common regional component with any other country in our sample, so its inflation is decomposed into a global and a country-specific component.

$$\begin{aligned}
Y_{i,t} &= \mu_t^{\text{Global}} + \mu_t^{\text{Regional}} + \epsilon_{i,t} + \psi_i \epsilon_{i,t-1}, & \epsilon_{i,t} &\sim \mathcal{N}(0, \sigma^2_{\epsilon,i}) \qquad (1)\\
\mu_t^{\text{Global}} &= \mu_{t-1}^{\text{Global}} + \beta_{t-1}^{\text{Global}} + w_{\mu,t}^{\text{Global}}, & w_{\mu,t}^{\text{Global}} &\sim \mathcal{N}(0, \sigma^2_{\mu,\text{Global}}) \qquad (2)\\
\beta_t^{\text{Global}} &= \rho_{\text{Global}} \beta_{t-1}^{\text{Global}} + w_{\beta,t}^{\text{Global}}, & w_{\beta,t}^{\text{Global}} &\sim \mathcal{N}(0, \sigma^2_{\beta,\text{Global}}) \qquad (3)\\
\mu_t^{\text{Regional}} &= \mu_{t-1}^{\text{Regional}} + \beta_{t-1}^{\text{Regional}} + w_{\mu,t}^{\text{Regional}}, & w_{\mu,t}^{\text{Regional}} &\sim \mathcal{N}(0, \sigma^2_{\mu,\text{Regional}}) \qquad (4)\\
\beta_t^{\text{Regional}} &= \rho_{\text{Regional}} \beta_{t-1}^{\text{Regional}} + w_{\beta,t}^{\text{Regional}}, & w_{\beta,t}^{\text{Regional}} &\sim \mathcal{N}(0, \sigma^2_{\beta,\text{Regional}}) \qquad (5)
\end{aligned}$$

We estimate the model's 20 deep parameters—the variances and moving average parameters—via maximum likelihood estimation (MLE).[2] To facilitate estimation, we reduce the dimension of the parameter space by calibrating some of the model's parameters. Specifically, we set $\sigma^2_{\mu,\text{Global}} = 0.01$ and $\sigma^2_{\beta,\text{Global}} = \sigma^2_{\beta,\text{Regional}} = 0.001$ to ensure that the global component has a smooth trend (Ahn and Luciani, 2024; Del Negro et al., 2019). In addition, we assume that the variances of the i.i.d. country-specific shocks are the same for countries in the same region. That is,

$$\begin{aligned}
&\sigma^2_{\epsilon,US} = \sigma^2_{\epsilon,CA}\\
&\sigma^2_{\epsilon,GE} = \sigma^2_{\epsilon,IT} = \sigma^2_{\epsilon,FR} = \sigma^2_{\epsilon,PT} = \sigma^2_{\epsilon,NE} = \sigma^2_{\epsilon,LU} = \sigma^2_{\epsilon,FI} = \sigma^2_{\epsilon,AU} = \sigma^2_{\epsilon,UK}
\end{aligned}$$

Finally, we set the variance of the observation errors to $\sigma_V^2 = 0.001$, a small value which

[2]We also explored the role of parameter uncertainty by assuming loose priors for the 20 parameters shown in Panel A of Table 1, and estimating their posterior distributions using an adaptive Markov Chain Monte Carlo algorithm similar to the one described in Beltran and Draper (2017). For these 20 parameters, the resulting posterior modes are nearly identical to their MLE estimates, and their respective Bayesian credible sets are extremely narrow, indicating that they are well-informed by the data. Using draws from the thinned MCMC chain of the posterior distribution of the deep parameters, we re-estimate the posterior means and variances of the forward-filtered-backward-smoothed state variables over time, and find that they are nearly identical to the ones presented in this paper using the MLE-based calibration.

facilitates the recursive estimation while ensuring a close fit to the observed core inflation series for each country.[3]

Table 1 reports the MLE values estimated for the deep parameters. The moving average coefficients ψ_i are close to 1 for many countries, indicating strong persistence. The variance of the North America regional level component is larger than that of the European regional level component. After fixing these deep parameters at their MLE values, we write the model in state-space form and estimate the posterior distributions of the regional, global, and country-specific components recursively forward in time using the Kalman Filter, starting with an uninformative prior at $t = 0$. Because we are interested in retrospective inspection of the state variables using the full sample period, we use a backward recursive (smoothing) algorithm to compute the conditional distributions of θ_t for any $t < T$ given the observations $y_{1:T}$, starting from the filtering distribution $\pi(\theta_T|y_{1:T})$. We ignore the estimated posterior means during the first 4 years of our sample to allow the Kalman filter to converge. Estimation details are provided in Appendix A.

Our objects of interest are the estimated means and variances of the posterior distributions of the state variables (the levels and growth rates of the global, regional, and country-specific components). Because we are interested in explaining past movements in inflation, we use the forward-filtered-backward-smoothed estimates of the state variables, which are smoother and more precise as they incorporate information from both the past and future observations.

3 Regional, global, and country-specific components

The estimated regional component for North America has historically behaved quite differently from the one for Europe. Figure 1a shows the estimated posterior means of the two regional components since 1975 and their respective 90% confidence intervals.[4] The Europe regional component was higher than the North America component through much of the

[3]Our model assumes that regional innovations are orthogonal. We examined the sensitivity of our findings to this assumption by estimating a version of our model in which we allow the Europe and North America regional innovations to be correlated. We find that our results are qualitatively unchanged.

[4]We treat the period from 1971 to 1974 as the training sample, and exclude the estimates of the posterior distributions of the state variables during this period from Figures 1a and 2a.

Table 1
Model Parameters

Panel A: Parameters Estimated Using Maximum Likelihood		
Parameter	Description	Estimate
$\sigma^2_{i,\text{Europe}}$	Variance of country shocks: GE, IT, FR, PT, NE, LU, FI, AU, UK	3.325
$\sigma^2_{i,\text{NorthAmerica}}$	Variance of country shock: US, CA	0.224
σ^2_{JP}	Variance of country shock: JP	0.153
σ^2_{Europe}	Variance of Europe regional shock	0.001
$\sigma^2_{\text{N.America}}$	Variance of North America regional shock	0.009
ψ_{GE}	MA coefficient for Germany	0.979
ψ_{IT}	MA coefficient for Italy	0.985
ψ_{FR}	MA coefficient for France	0.929
ψ_{PT}	MA coefficient for Portugal	0.856
ψ_{NE}	MA coefficient for Netherlands	0.964
ψ_{LU}	MA coefficient for Luxembourg	0.894
ψ_{FI}	MA coefficient for Finland	0.843
ψ_{AU}	MA coefficient for Austria	0.984
ψ_{UK}	MA coefficient for United Kingdom	0.988
ψ_{CA}	MA coefficient for Canada	0.648
ψ_{US}	MA coefficient for United States	0.956
ψ_{JP}	MA coefficient for Japan	0.752
ρ_{Europe}	AR1 coefficient for Europe growth rate shock	0.970
$\rho_{\text{N.America}}$	AR1 coefficient for N.Amer. growth rate shock	0.967
ρ_{Global}	AR1 coefficient for global growth rate shock	0.957
Panel B: Calibrated Parameters		
Parameter	Description	Value
σ^2_V	Variance of observation error (same for all countries)	0.001
$\sigma^2_{\mu,\text{Global}}$	Variance of global level shock	0.01
$\sigma^2_{\beta,\text{Global}}, \sigma^2_{\beta,\text{Regional}}$	Variance growth rate shocks (Global, Europe, N.Amer.)	0.001

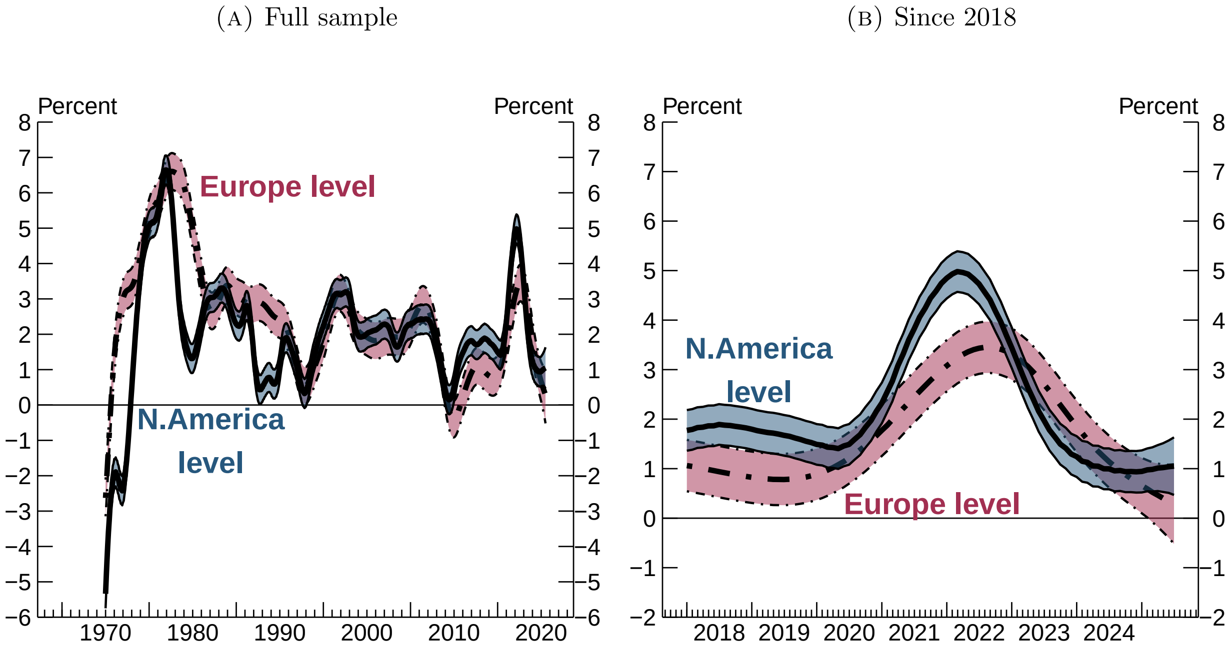
Note. Panel A reports the estimated parameters of the dynamic linear model. Panel B reports externally calibrated parameters.

1970s and 1980s. From the late 1990s through 2019, however, both components were at similar levels.

More recently, as seen in Figure 1b, the regional components diverged again. The North America component took off in 2021 and fell back the following year. Europe's regional component of core inflation also increased in 2021, but not as sharply as the North

Figure 1

Europe and North America Regional Components



Note. Thick solid line and thick dot-dashed line show the estimated posterior means of the North America and Europe regional components, respectively. The thin solid and thin dot-dashed lines denote the edges of their respective 90% confidence intervals. Panel (A) plots these components from January 1975 to July 2025. Panel (B) plots these components since 2018.

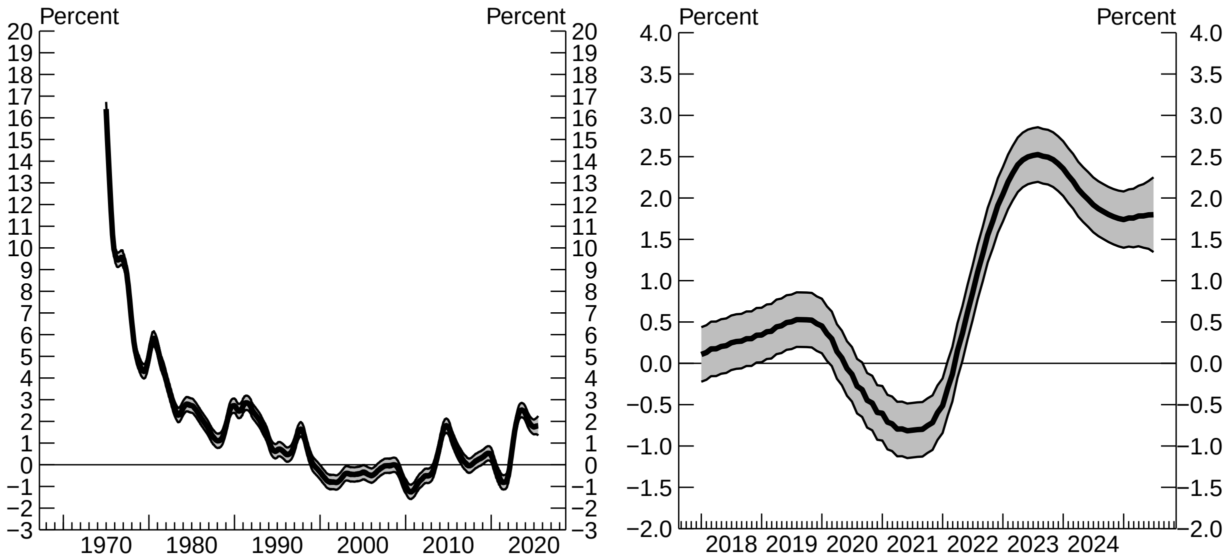
America component. And although the North America component was declining in 2022, the European component continued to rise that year.

The mean of the posterior distribution of the "global" component of core inflation is shown in Figure 2a. The global component of core inflation peaked in the 1970s and gradually declined through the 2000s. After the COVID pandemic, as shown in Figure 2b the global component rose sharply. The global component then partially retraced to still-elevated levels as of July 2025.

Our model includes the growth rates of the global and regional components as state variables that vary over time, allowing us to assess the degree to which the global and regional components of inflation accelerated or decelerated following the COVID pandemic. As shown in Figure 3a, the global component's growth rate turns negative when the pandemic arrives in 2020, then shoots up as the global economy begins to reopen, before

Figure 2
Global Component Over Time

(A) Full sample (B) Since 2018



Note. Thick line shows the estimated posterior mean of the global component of core inflation. Thin lines denote the edges of its 90% confidence intervals. Panel (A) shows the global component from January 1975 to July 2025. Panel (B) shows the global component since 2018.

decelerating. The current growth rate has returned to zero, consistent with the flattening out of the global component at its still-elevated level. Figure 3b compares the growth rates of the regional components and shows a sharper acceleration and deceleration in core inflation in North America relative to Europe. While the North America growth rate has returned to zero, the growth rate in Europe remains negative, consistent with continued disinflation.

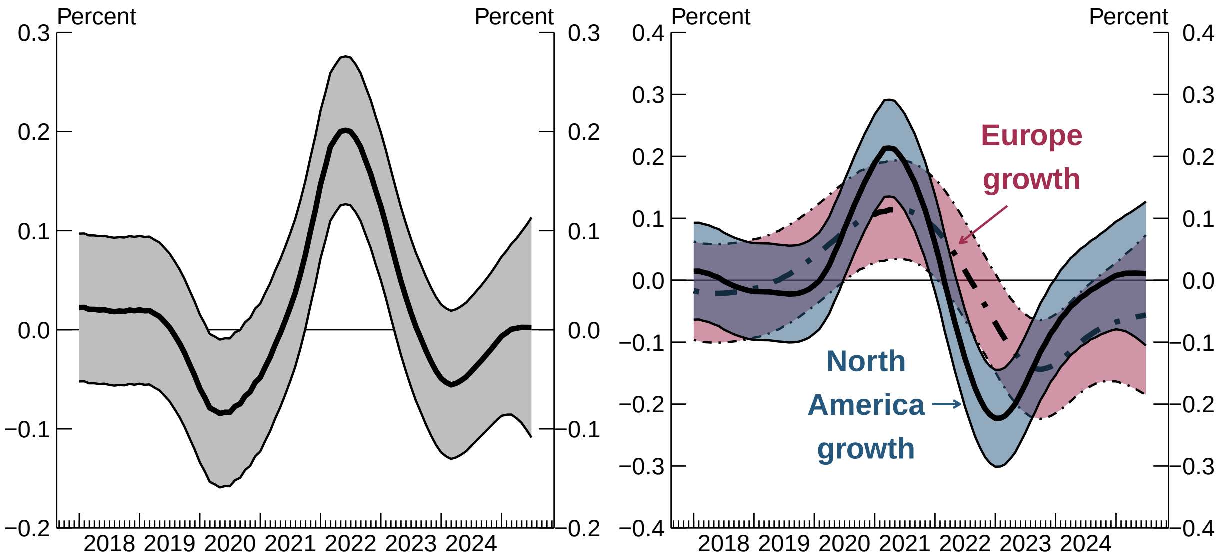
Figure 4 decomposes core inflation for the U.S., U.K., Canada, and France into the global, regional, and country-specific components described earlier.[5] The country-specific components generally contribute less than the other components (with the exception of the U.K.), and are more volatile as they capture the higher-frequency noise in core inflation for each country. The country components also reflect differences in levels of core inflation between countries in the same region. For example, UK's core inflation was higher than

[5]Appendix B contains similar figures for the other 8 countries in our sample not shown here.

Figure 3

Growth Rates of Global and Regional Components, β_t^{Global} and $\beta_t^{Regional}$

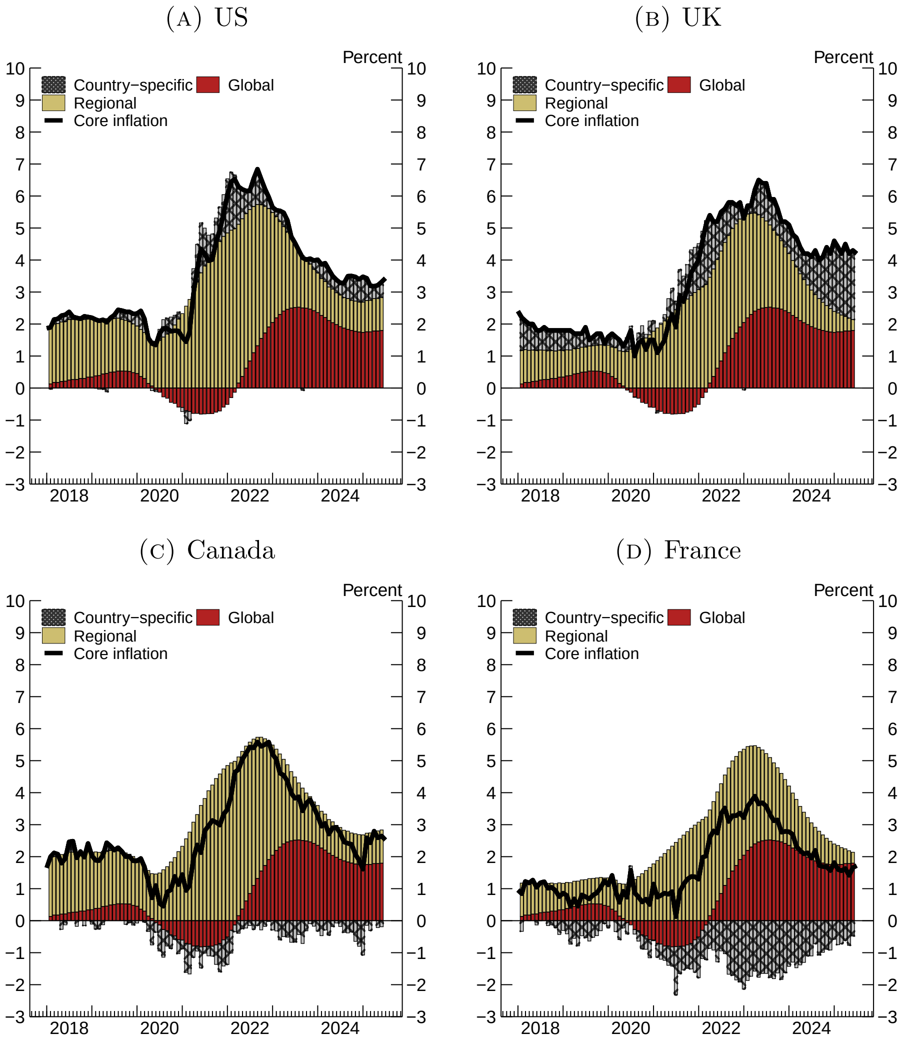
(A) Growth rate global component (B) Growth rate of regional components



Note. Panel (A) shows the growth rate of the global component, β_t^{Global}, with the thick line denoting the posterior mean of the growth rate, and the thin lines denoting the edges of the 90% confidence intervals. Panel (B) shows the growth rates of the North America and Europe regional components, $\beta_t^{N.Amer.}$, and $\beta_t^{Eur.}$. Thick solid line and thick dot-dashed line show the estimated posterior means of the growth rates of the North America and Europe regional components, respectively. Thin solid and thin dot-dashed lines denote the edges of their respective 90% confidence intervals.

that of the other European countries in our sample, resulting in a large positive country-specific component estimated for the UK. The opposite is true for France, which has had smaller rates of core inflation relative to the rest of Europe. In North America, the estimated country-specific component for the U.S. rises sharply in 2021, reflecting the sharper increase in U.S. core inflation relative to Canada's core inflation.

Figure 4
Core Inflation Decomposition for Selected Countries



Note. Each panel decomposes core inflation for a given country. The solid black line is 12-month core inflation, also equal to the sum of the components. The light-shaded bars represent the regional component, the dark-shaded bars the global component, and the cross-hatched bars the country-specific component.

4 Explaining the post-COVID surge in U.S. core inflation

Having extracted the regional, country-specific, and global components of core inflation for each country, we next examine their economic drivers, focusing on the global component and the North America regional component, which are the two largest components from the decomposition of U.S. core inflation shown in Figure 4. We start by examining the drivers of the global component, which is relatively large and shared by the other countries in our sample. Because our estimated global component is assumed to follow a random walk, our dependent variable is the 12-month change in the estimated global component.

4.1 Drivers of the global component of U.S. core inflation

To understand the drivers of the global component, we regress the 12-month change in the global component on a broad set of explanatory variables related to global forces, such as global energy prices, supply frictions, and labor market tightness. To arrive at a parsimonious model, we adopt a general-to-specific model selection strategy that begins with a 'general unrestricted model' (GUM) that encompasses the essential characteristics of the underlying data, and then eliminate variables that are statistically insignificant using Autometrics, which is part of the software package PcGive-OxMetrics (Doornik, 2009; Hendry and Doornik, 2009).[6] Our fully-specified GUM includes the following variables in their levels and changes, as well as their lags: global supplier delivery times, global manufacturing backlogs, sea freight shipping costs, brent crude spot price, and the average of the unemployment gap for the countries in our sample. It also includes a constant, trend, and 1-year and 2-year lags of the dependent variable.[7] We underscore that this is our own research analysis based on our particular methodology and that different methodologies may produce different results. In particular, our reduced form approach treats the regressors as exogenous variables and their changes as structural shocks, when in reality they are likely endogenously determined. Thus, our results do not imply causality and should be

[6] Autometrics uses a tree-search algorithm to detect and eliminate statistically-insignificant variables, avoiding path-dependence. At any stage, a variable is only removed if the new model encompasses the GUM. The terminal model is, by design, a statistically well-specified valid reduction of the GUM (Doornik, 2008).

[7] See Data Appendix for a description of the variables considered in the GUM.

Table 2
Drivers of Changes in Global Component

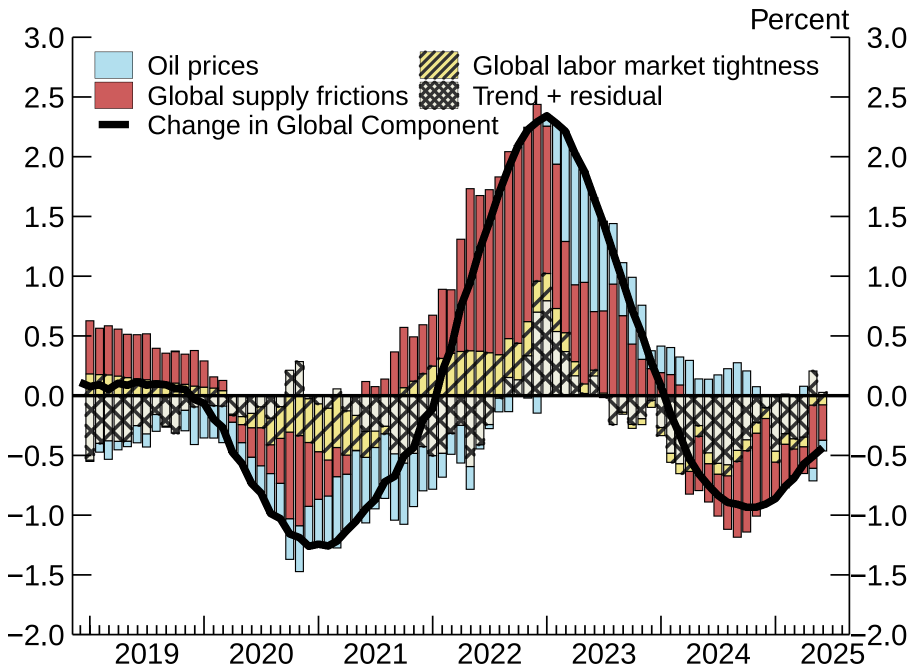
	Estimate	HACSE
Unemployment gap_t	-0.27816^{***}	0.072151
Change in sea freight costs_t	0.027515^{***}	0.0071516
Change in sea freight costs_{t-12}	0.033495^{***}	0.0052750
Manuf. backlogs_{t-6}	0.040985^{***}	0.017491
Change Brent crude spot_t	0.0027519^{**}	0.0013871
Change Brent crude spot_{t-24}	0.0028226^{***}	0.0011110
Brent crude spot_{t-12}	0.018710^{***}	0.0032281
Trend	-0.0023692^{***}	0.00053646
Number of observations: 235		
Adjusted R-squared: 0.7713		
F-statistic: 113.8		

Notes. Ordinary least squares regression coefficients and their heteroskedasticity and autocorrelation consistent standard errors (HACSE). Dependent variable is 12-month change in the estimated global component. Changes computed on a 12-month basis. All variables are demeaned. The regression is estimated from December 2005 through June 2025. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.
Source. OECD Main Economic Indicators, S&P Global Purchasing Manager's Index (PMI), Current Population Survey, Producer Price Index, Organization of the Petroleum Exporting Countries, Japan Ministry of Health Labor and Welfare, Statistics Canada, Instituto Nazionale di Statistica, INSEE, Deutsche Bundesbank, UK Office for National Statistics, Statistics Austria, Instituto Nacional de Estatistica, Statistics Finland, Luxembourg Central Service of Statistics and Economic Studies, Statistics Netherlands; all via Haver Analytics.

interpreted merely as suggestive evidence of the underlying drivers.

The results are presented in Table 2. All coefficients are statistically significant at the 1% level, and the adjusted R-squared of 0.77 indicates a good overall fit. The negative coefficient on the unemployment gap suggests that the global component is associated with overall labor market tightness in the advanced economies in our sample. The positive coefficients on changes in sea freight shipping costs and manufacturing backlogs suggests that global supply frictions also drive the global component. The positive coefficient on lagged changes and level of Brent crude oil prices is consistent with second-round effects of higher energy prices (Alp et al., 2023). There is also a small, negative trend over time. Figure 5 shows the relative contributions of the drivers since 2019. The post-covid surge in the global component is largely explained by global supply frictions as measured by changes in sea freight costs and global manufacturing backlogs, and to lesser degree, past energy shocks and overall tightness in labor markets across the countries in our sample.

Figure 5
Drivers of Changes in Global Component



Notes. This decomposition uses the estimated coefficients shown in Table 2, and groups the contributions of the right hand side variables by broad category. 'Supply frictions' include change in sea freight costs and manufacturing backlogs.

4.2 Drivers of changes in the North America component

We run a similar exercise to explain changes in the North America regional component, using data for the U.S. and Canada to construct regional averages of variables that measure labor market tightness and changes in consumption and savings.[8] Specifically, we regress the 12-month change in the North America component on regional measures of tightness in labor and goods markets, while controlling for its own lags, a constant, and a time trend.[9] The estimated coefficients are shown in Table 3. The results suggest that the North America component is largely driven by tightness in U.S. and Canadian labor markets (change in job-openings-to-unemployment ratio and average weekly earnings), and lagged changes in households' savings behavior (as excess savings during the pandemic boosted consumption spending).

[8]We ran a similar regression to explain the 'non-global' part of U.S. core inflation by replacing the dependent variable with the sum of the 12-month change in the North America regional and U.S. country-specific components (using the same explanatory variables) and found similar results.

[9]See Data Appendix C for full list of explanatory variables considered in the GUM.

TABLE 3
Drivers of Changes in North America Component

	Estimate	HACSE
Change openings-to-unemp. $\text{ratio}_t^{N.Amer.}$	2.8512 ***	0.35003
Change avg.weekly $\text{earnings}_t^{N.Amer.}$	0.21601 ***	0.098672
Change personal savings $\text{rate}_{t-12}^{N.Amer.}$	0.089840 ***	0.018180
Number of observations: 108		
Adjusted R-squared: 0.7689		
F-statistic: 179		

Note. Ordinary least squares regression coefficients and their heteroskedasticity and autocorrelation consistent standard errors (HACSE). Dependent variable is 12-month change in the estimated North America component. Changes computed on a 12-month basis. All variables are demeaned. The regression is estimated from April 2016 through March 2025. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.
Source. OECD Main Economic Indicators, Current Employment Statistics, Current Population Survey, Job Openings and Labor Turnover Survey, National Income and Product Accounts; all via Haver Analytics.

Figure 6 shows the relative contributions of the drivers since 2019. The post-Covid surge in the North America component is largely explained by tightness in regional labor markets, and to lesser degree, excess savings during the pandemic which boosted consumption spending of lower-income households.[10]

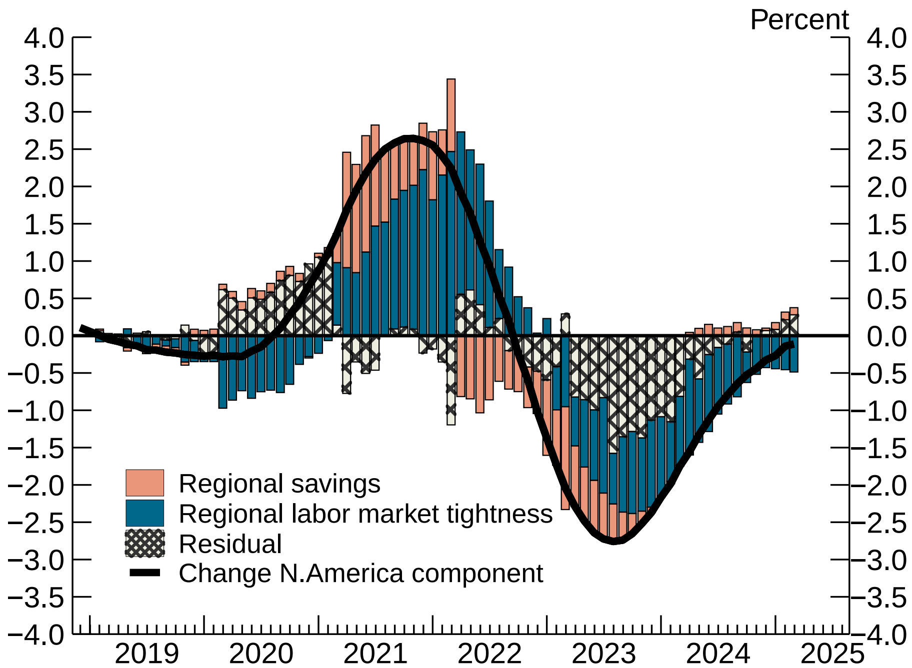
5 Conclusion

We examine the international co-movement of core inflation from a regional perspective, using a Bayesian dynamic linear model that decomposes core inflation rates in the major advanced economies since the 1970s into global, regional, and country-specific components. We find that the post-pandemic surge in the global component largely reflected global supply frictions and to a lesser degree, past energy price shocks and overall tightness in labor markets across many countries. Meanwhile, the surge in the North America component was associated with tightness in labor markets and lagged changes in households' savings behavior.

Our model is optimized for decomposing and explaining past movements in inflation,

[10] Aladangady et al. (2022) find that spending among households in the bottom half of the income distribution rises by about 10 percent above its pre-pandemic trend following the CARES Act in 2020 and remains well above trend through 2022.

Figure 6
Drivers of Changes in North America Component



Notes. This decomposition uses the estimated coefficients shown in Table 3 and groups the contributions of change in openings-to-unemployment and average weekly earnings into the labor market tightness category. Explanatory variables are the averages for the U.S. and Canada.

not for forecasting future inflation observations. That said, the Bayesian framework easily allows one to compute the predictive densities of both the state variables and the observables k-steps ahead sequentially using recursive algorithms. The strong persistence in both the levels and the growth rates of the global, regional, and country-specific components should, in principle, facilitate out-of-sample forecasting. Further research could explore how to optimize models of this nature to produce reliable out-of-sample forecasts. Finally, although we focus on a dozen advanced economies with similar inflation experiences over the last 50 years, our model could easily be extended to include more countries.

Our results could have implications for monetary policy. Monetary policy could be challenging when the global and regional components of core inflation are moving in opposite directions. For example, in the second half of 2022, the regional component of US core inflation had leveled off and was starting to decline, but this decline was masked by continued increases in the global component, leaving overall core inflation largely unchanged, at elevated levels.[11]

[11] In a speech at the time, Federal Reserve Chair Jerome Powell acknowledged that core inflation had "mainly moved sideways" and that "despite tighter policy and slower growth over the past year, we have not seen clear progress on slowing inflation." Jerome H. Powell, 2022, "Inflation and the labor market", speech delivered at the Hutchins Center on Fiscal and Monetary Policy, Brookings Institution, Washington D.C., November 30, https://www.federalreserve.gov/newsevents/speech/powell20221130a.htm

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A Dynamic Linear Model Representation

A dynamic linear model is specified by a Normal prior distribution for the p-dimensional state vector θ at time $t = 0$, $\theta_0 \sim \mathcal{N}_p(m_0, C_0)$, and the following equations that govern the evolution of the state-space system for each time $t \geq 1$:

$$\begin{aligned} Y_{i,t} &= F\theta_{i,t} + v_{i,t} \qquad v_{i,t} \sim \mathcal{N}(0, V_i) \\ \theta_{i,t} &= G\theta_{i,t-1} + w_{i,t} \qquad w_{i,t} \sim \mathcal{N}(0, W_i), \end{aligned}$$

where the $p \times p$ matrix $G - t$ and the $m \times p$ matrix F_t are known and $v_{i,t}$ and $w_{i,t}$ are independent Gaussian random vectors with mean zero and known, constant variances V_i and W_i (Petris et al., 2009).

We next define the building blocks of the model and combine them into a single multivariate model.

(a) The MA(1) component for each country is defined as follows.

$$Y_{i,t} = \varepsilon_{i,t} + \psi_i \varepsilon_{i,t-1} \qquad \mathcal{N}(0, \sigma^2_{Y,i})$$

The MA components are modeled as two separate state variables, $\theta_{1,t}$ and $\theta_{2,t}$, with:

$$F = \begin{bmatrix} 1 & 0 \end{bmatrix}, \qquad V = 0 \tag{A.1}$$

$$G = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \qquad W_i = \begin{bmatrix} 1 & \psi_i \\ \psi_i & \psi_i^2 \end{bmatrix} \sigma^2_{w,i} \tag{A.2}$$

(b) Global and regional components

The global mean (μ_t^{Global}) and two regional time-varying means (μ_t^{Europe}, $\mu_t^{\text{NorthAmerica}}$) are unobserved state variables that follow random walks with a time-varying growth rate. These time varying growth rates, in turn, follow an auto-regressive process of order 1.

Combining the moving average components with the global and regional means, the full model is specified as follows.

Define Y_t as the vector of observable 12-month core inflation rates (π_t) for the 12 countries in our sample:

$$Y_t = (\pi_t^{\mathrm{GE}}, \pi_t^{\mathrm{IT}}, \pi_t^{\mathrm{FR}}, \pi_t^{\mathrm{PT}}, \pi_t^{\mathrm{NE}}, \pi_t^{\mathrm{LU}}, \pi_t^{\mathrm{FI}}, \pi_t^{\mathrm{AI}}, \pi_t^{\mathrm{UK}}, \pi_t^{\mathrm{CA}}, \pi_t^{\mathrm{US}}, \pi_t^{\mathrm{JP}})'$$

F is a matrix of dimension 12×30. The first 24 columns contain the F matrix defined in Equation A.1, spanning two columns for each row. Column 25 of F corresponds to the global mean shared by every country, so it contains a 1 on every row. Column 27 of F corresponds to the Europe regional mean shared by the 9 European countries in our sample, so it contains a 1 on rows $1-9$. Column 29 of F corresponds to the North America regional mean, shared by the US and Canada, so it contains a 1 on rows 10 and 11.

$$F = \begin{bmatrix} 1 & 0 & \dots & 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & \dots & 1 & 0 & 1 & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & \dots & 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & \dots & 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & \dots & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & \dots & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & \dots & 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

G is a matrix of dimension 30×30, with the first 24 columns containing the G matrix defined in Equation A.2 along the diagonals. The last 6 columns of GG specify that the global and regional components follow a random walk and their respective growth rates follow an AR(1) process.

$$G = \begin{bmatrix} 0 & 1 & \dots & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & \dots & 0 & \rho_{Gl.} & 0 & 0 & 0 & 0 \\ 0 & 0 & \dots & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & \dots & 0 & 0 & 0 & \rho_{Eur.} & 0 & 0 \\ 0 & 0 & \dots & 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & \dots & 0 & 0 & 0 & 0 & 0 & \rho_{N.Amer.} \end{bmatrix}$$

W is a matrix of dimension 30×30. The variances of the shocks to each country's moving average components are along the diagonals of the first 24 rows, given by the 2×2 W_i matrix defined in Equation A.2. The variances of the global, Europe, and North America components, as well as the variances of their respective growth rates are in the last 6 diagonal elements of W.

$$W = \begin{bmatrix} W_i & \dots & 0 & 0 & 0 & 0 & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \dots & \sigma^2_{\mu,\text{Global}} & 0 & 0 & 0 & 0 & 0 \\ 0 & \dots & 0 & \sigma^2_{\beta,\text{Global}} & 0 & 0 & 0 & 0 \\ 0 & \dots & 0 & 0 & \sigma^2_{\mu,\text{Eur.}} & 0 & 0 & 0 \\ 0 & \dots & 0 & 0 & 0 & \sigma^2_{\beta,\text{Eur.}} & 0 & 0 \\ 0 & \dots & 0 & 0 & 0 & 0 & \sigma^2_{\mu,\text{N.Amer}} & 0 \\ 0 & \dots & 0 & 0 & & 0 & 0 & \sigma^2_{\beta,\text{N.Amer.}} \end{bmatrix}$$

Our objects of interest are the time-varying means of the posterior distributions of the levels and growth rates of the global, regional, and country-specific components, and their 90% confidence intervals. For a given country, the posterior means of each component adds up to the level of 12-month core inflation; the unexplained residual in the observed series is negligibly small by construction.

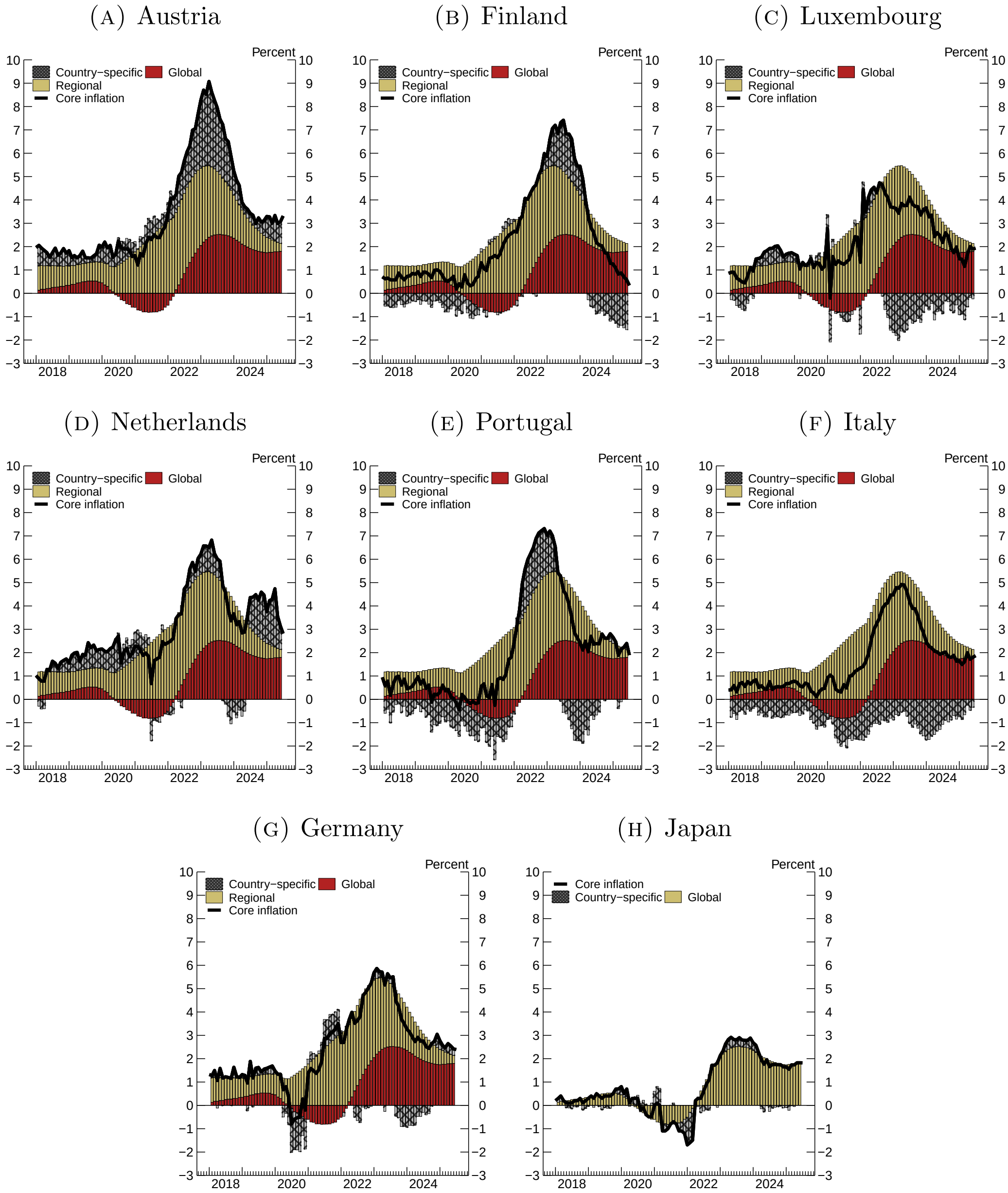
All relevant marginal and conditional distributions are Gaussian, and completely determined by their means and variances (Petris et al., 2009). The solution to the filtering problem for DLMs is given by the Kalman Filter. As described in Petris et al. (2009), the conditional distribution of the state variables given the full-information sample $y_{1:T}$ is also Gaussian, and we compute the forward-filtered-backward-smoothed (two-sided, full sample) estimates using the Kalman smoother. Although the posterior variances can be updated sequentially using the Kalman filter and Kalman smoother, computation suffers from numerical instability and possibly non-symmetric or even negative definite calculated variances. We use the 'dlm' package in R (Petris, 2010; Petris et al., 2009) because it has a robust algorithm for calculating the posterior variances by sequentially updating the singular-value decomposition.

The Bayesian approach allows us to choose the prior mean for the state vector θ_t at $t = 0$. To calibrate our priors, we use the global and regional averages of the 12-month core inflation rates from December 1970 (before the start of our estimation period), with wide confidence bands to make them less informative. The priors for the state vector is specified below. Our dataset is large, with 655 monthly observations for 12 countries. The priors are swamped by the data such that the results are insensitive to the choice of priors. For example, setting all the prior means to zero produces nearly identical results.

$\mu_0^{Global} = \mathcal{N}(2.48, 10),$
$\mu_0^{Europe} = \mathcal{N}(2.26, 10),$
$\mu_0^{N.America} = \mathcal{N}(2.04, 10),$
$\mu_0^{JP} = \mathcal{N}(4.65, 10),$
$\mu_0^{i} = \mathcal{N}(0, 10) \forall i \in (GE, IT, FR, PT, NE, LU, FI, AI, UK, CA, US).$

B Core Inflation Decomposition for Selected Countries

Figure B.1
Core Inflation Decomposition for Selected Countries



Note. Each panel decomposes core inflation for a given country. The solid black line is 12-month core inflation, also equal to the sum of the components. The light-shaded bars represent the regional component, the dark-shaded bars the global component, and the cross-hatched bars the country-specific component.

C Data used in regressions

The explanatory variables used in the model selection process for the regressions in Section 4 are listed in Table C.1 below. Both the levels and changes in these variables are included in the general unrestricted model (GUM). All are sourced from Haver Analytics.

TABLE C.1
Data series used in regressions in Section 4

Description	Haver series name
UK Brent crude spot, $ per barrel	MGBUKB@ENERGY
Global manuf. suppliers' delivery times, index	SGBLMD@MKTPMI
Global manuf. backlogs of work, index	SGBLMB@MKTPMI
Global manuf. new orders, index	SGBLMO@MKTPMI
U.S. PPI deep sea freight transportation, index	R483111@PPIR
U.S. PPI deep sea freight transportation, index	R483111@PPIR
Personal Consumption Expenditures: Goods, SAAR, Bil.$	CTGBM@USECON
JOLTS: Job Openings: Total, SA, Thousands	LJJTLA@USECON
Unemployment, 16yr+, SA,Thousands	LTU@USECON
Civilian unemployment rate, 16yr+, SA %	LR@USECON
Civilian participation rate, 16yr+, SA %	LP@USECON
Personal savings rate, SA, %	YPSVRM@USECON
Univ. of Michigan: Exp. infl. rate next year, %	CINF1@USECON
Avg. hours at Work: 16+ NSA, Hrs	LENCLWHN@USECON
Avg. hrly earnings: Pvt Sector SA, $/Hr	AWBWPA@USECON
Real disposable pers. income, SAAR, Bil.Chn.2017$	YPDHM@USECON
Real retail sales and food services, SA, Mil.1982-84$	NRSTH@USECON
Government Social Benefits to Persons, SAAR, Bil.$,	GTPFM@USECON

To construct the unemployment gap used in the regression of the global component, we first collect unemployment rates for the countries in our sample from Haver. Table C.2 lists the unemployment rate series. Next, we average across countries to obtain an averaged unemployment rate,

$$urate_t = \frac{1}{12}\sum_j urate_{jt}.$$

We define the unemployment gap as the 12-month change of the 12-month average unemployment rate (Stock and Watson, 2021),

$$ugap_t = urate_t - urate_{t-12}.$$

Table C.2
Unemployment rates

Country	Haver series name
Japan	S158ELUR@G10
U.S.	S111ELUR@G10
Canada	S156ELUR@G10
UK	S112ELUR@G10
France	S132EURH@G10
Italy	S136ELUR@G10
Austria	ATNELCR@ALPMED
Portugal	S182UR@G10
Finland	H172ELUR@G10
Luxembourg	S137ELUR@G10
Netherlands	S138ELUR@G10
Germany	DESE315@GERMANY