CHAPTER 2

THE GREAT TIGHTENING: INSIGHTS FROM THE RECENT INFLATION EPISODE – ONLINE ANNEXES

Online Annexes 2.1-2.4 provide details regarding data sources, methodology, and complementary results presented in the main text.

Online Annex 2.1. Data Sources and Variables

This section provides a detailed description of the two primary datasets used in the chapter, with information on data sources and variable transformations.

2.1.1. Country-level quarterly dataset:

Output measures: GDP and potential output data, sourced from the World Economic Outlook (WEO) database, are presented in both current and constant prices. Seasonally adjusted consumption expenditure data are from the Organisation for Economic Co-operation and Development (OECD) Quarterly National Accounts database. We calculate goods consumption by deducting service consumption from total household consumption provided by the OECD.

Prices: Inflation measures such as the Consumer Price Index (CPI) and core CPI are primarily retrieved from the WEO database, supplemented by Haver Analytics. Core goods (excluding foods and energy) and services CPI are based on updates from the Haver dataset, initially collected by Gudmundsson and others (2024). Commodity price indices are obtained from the IMF Primary Commodity Prices System Database. These commodity indices are weighted averages of select commodity price indices, based on identified benchmark prices that are representative of the global market. The weight is based on the global import share over a 3-year period (2014-2016) and normalized to 100 at year 2016 prices.

Labor markets: Wage data are based on updates from the dataset created by the October 2022 WEO Chapter 2 "Wage Dynamics Post–COVID-19 and Wage-Price Spiral Risks". The primary sources on wages are combined by taking one of the sources as the primary and extending backwards and forwards using growth rates from the other available sources. Where available, data from the OECD is taken first, followed by data from the International Labour Organization (ILO), and other sources such as Eurostat, Haver Analytics, and US Bureau of Labor Statistics. We construct four wage series: hourly wage in local currency, hourly wage index, wage per worker in local currency, and wage per worker index. For quarterly frequency, wages in local currency are annualized.

Policy rates: Central bank policy rates are collected from the Bank for International Settlements (BIS). We select end-of-period monthly rates to convert into quarterly data (that is, for the first quarter, the March observation is used). The selection of policy rates, such as target, repo, or discount rates, is done by BIS collaboration with national central banks. In instances where monetary policy did not use an interest rate instrument, BIS dataset includes the most referenced money market or central bank rates.

Others: Global Supply Chain Pressure Index (GSCPI) data are from the Federal Reserve Bank of New York. GSCPI readings measure standard deviations from the index's historical average. Data on the share of primary energy consumption that comes from oil/gas are collected from the Energy Institute - Statistical Review of World Energy (2024), with major processing by Our World in Data. The data are measured as a percentage of the total primary energy, using the substitution method. Oil supply news shocks data are collected from: https://github.com/dkaenzig/oilsupplynews and are based on the VAR of Känzig (2021). We add up the monthly oil supply news shocks data in each quarter to construct the quarterly data.

Online Annex Table 2.1.1. Country Groups Composition for Advanced and Emerging Markets in Country-Level Quarterly Dataset

Advanced Economies	Emerging Markets
Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Italy, Japan, Korea, Latvia, Lithuania, Netherlands, New Zealand, Norway, Portugal, Slovak Republic, Slovenia, Spain, Sweden, United Kingdom, United States	Bulgaria, Brazil, Chile, China, Colombia, Hungary, Indonesia, Mexico, Poland, Romania, Russia, South Africa, Türkiye

Source: IMF staff compilation.

2.1.2. Country-level sectoral quarterly dataset:

Our dataset uses the OECD 11-sector classification, central to the productivity by industry dataset, as the primary method for sector classification, integrating Gross Value Added (GVA) data sourced from the OECD. This classification adheres to the International Standard Industrial Classification of All Economic Activities, Revision 4 (ISIC Rev. 4), which groups industries based on shared characteristics such as the nature of the goods and services produced, their usage, and the inputs and processes involved in their production. We map these OECD sectors to the corresponding NACE Rev.2 classification at the section level (a first level consisting of headings identified by an alphabetical code), ensuring alignment in sector description and classification. This allows us to incorporate Producer Price Index (PPI) data from Eurostat. For instance, the OECD sector 'B_E', which aggregates mining, manufacturing, energy, and water activities, corresponds to Eurostat's PPI classifications under heading 'B_E36'. When data at the first level are unavailable from Eurostat, we use weighted aggregation of second-level data as provided by Eurostat. Additionally, we distinguish sector 'C' (Manufacturing) from the broader 'B_E' category to derive the 'BDE' sector (excluding 'C') to avoid sector overlap for our analysis. To map OECD sectors to the US Bureau of Economic Analysis (BEA) sector classifications, we manually match sectors based on the sector descriptions from the BEA "value-added by industry" data file, aggregating multiple BEA sectors into broader OECD categories when they share production processes, goods, services, and technological uses. This allows us to incorporate US value added data from BEA.

Online Annex Table 2.1.2. Country Groups Composition and Sector Definitions in Country-Level Sectoral Quarterly Dataset

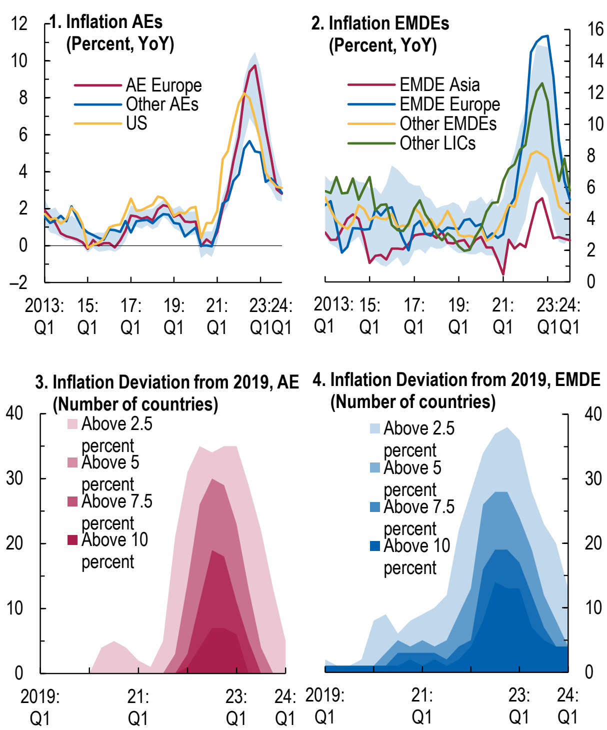
Advanced Economies	Emerging Markets	Sectors
Austria, Belgium, Croatia, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States	Bulgaria, Brazil, Chile, Colombia, Costa Rica, Hungary, Poland, Romania, Türkiye	**Sector A:** Agriculture, forestry and fishing **BDE:** Industry, excluding manufacturing **C:** Manufacturing **F:** Construction **G_I:** Distributive trade, repairs; transport; accommodation; food service activities **J:** Information and communication **K:** Financial and insurance activities **L:** Real estate activities **M_N:** Professional, scientific, technical activities; administrative, support service activities **O_Q:** Public administration; compulsory social security; education; human health **R_U:** Other service activities

Source: IMF staff compilation.

Online Annex 2.2. Additional Stylized Facts

Online Annex Figure 2.2.1 provides further details on the distribution of the global inflation surge. European countries (AEs and EMDEs) were relatively more affected by the inflation while other AEs (mostly in Asia) and Asian EMDEs witnessed notably lower inflation (Panels 1-2). Throughout, the dynamics were highly synchronized across countries with more than 50 countries (out of 80 AEs and EMDEs) witnessing inflation rises of more than 5 percent relative to 2019 (Panels 3-4).

Online Annex Figure 2.2.1. Distribution of Inflation Surge across Countries



Sources: Haver Analytics; and IMF staff calculations.
Note: In panel 1 and 2, lines are the median of CPI inflation within each analytical group. The bands depict the 25th to 75th percentiles of data across economies. Panel 3 and 4 show the number of countries above certain levels of inflation deviation from the averaged 2019 inflation within each analytical group, with a sample of 37 AE countries and 43 EMDE countries. AEs = advanced economies; EMDEs = emerging market and developing economies; LICs = low-income countries. YoY = year-over-year.

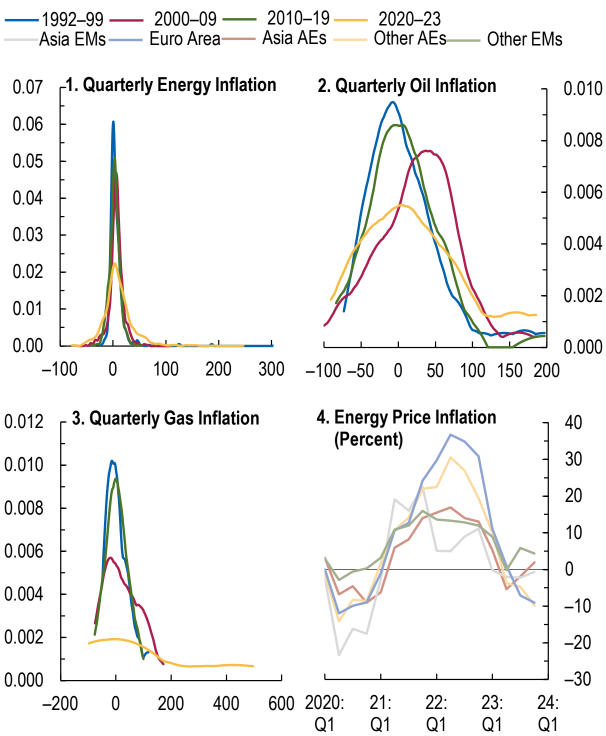
Several features of the energy price shock during 2020-2023 stand out. First, the shocks were extraordinarily large in comparison to prior decades as evidenced by the long right tail of the distribution of energy price changes over 2020-2023 (Online Annex Figure 2.2.2, Panel 1). These large energy shocks were not primarily driven by oil – whose fluctuations were broadly in line with historical oil price fluctuations (Online Annex Figure 2.2.2, Panel 2) but much more by gas prices (Panel 3) and coal.

Finally, there were important regional differences in the extent of energy inflation with energy inflation peaking at close to 40 percent in advanced economies while economies in Asia were much less affected (Panel 4).

As shown in Figures 2.3 and 2.5, inflation was initially driven by more energy-dependent and by more flexible price sectors. The raw correlation of these two characteristics (using cross-country data) is .43. Hence, there is overlap but also independent variation between those two characteristics. Online Annex Figure 2.2.3 shows that among sectors with high energy-dependence, inflation took off faster and peaked much higher in more price flexible sectors, highlighting how these two sectoral characteristics interact. Conversely, among sectors with low energy dependence, inflation evolved more in parallel between high and low price flexibility sectors, albeit inflation rose higher in the more price flexible ones.

Online Annex Figure 2.2.2. Distribution of Energy Price Shocks and Regional Differences during 2020–2024

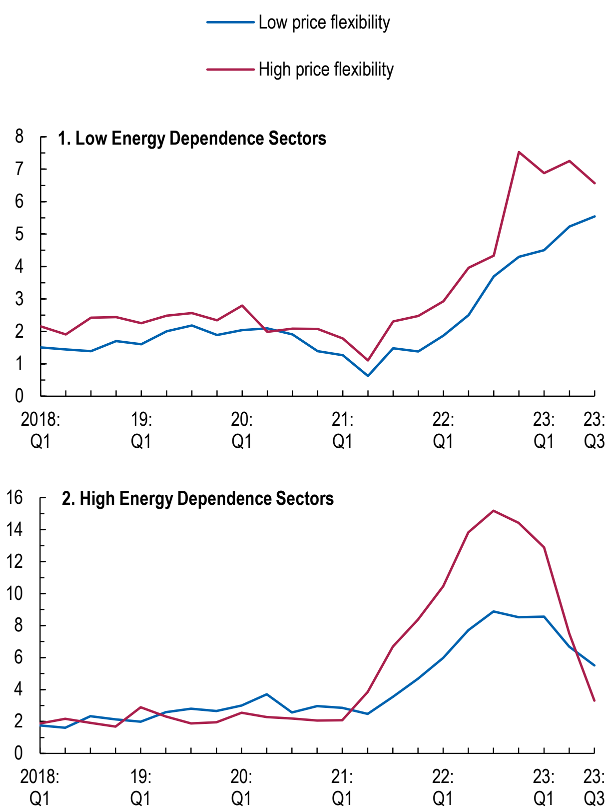
(Density, unless noted otherwise)



Sources: Haver Analytics; IMF, Primary Commodity Price System; and IMF staff calculations.
Note: Panels 1–3 report distribution of quarterly energy, oil, and gas price inflation using estimated kernel densities. Panel 4 reports year-on-year energy inflation across regions. AEs = advanced economies; EMs = emerging markets.

Online Annex Figure 2.2.3. Sectoral Inflation across Sectors with High/Low Energy Dependence and High/Low Price Flexibility

(Percent, year over year rate)



Sources: Haver Analytics; Organisation for Economic Co-operation and Development, and IMF staff calculations.
Note: Energy dependence is computed as the total input share of oil, gas, and utilities in intermediates. Price flexibility is measured using data from Rubbo (2023). Sectors are split along the median of energy dependence and then along the median of price flexibility. Sectoral inflation rates are then collapsed as medians across groups.

Energy Price Passthrough

To formally estimate the passthrough of energy price inflation into CPI inflation and whether this has changed during the pandemic, we estimate the following local projections specification with an interaction term for the impact of energy inflation on CPI inflation post-Covid.

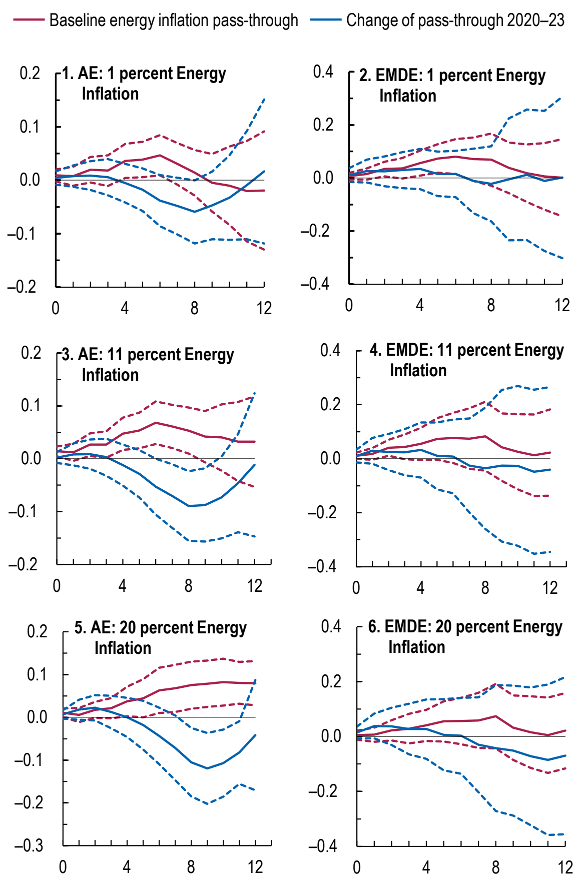
$$\pi^{CPI}_{j,t+h} = \alpha^h_j + \beta^h \, \pi_{energy,j,t-1} + \gamma^h \, \pi_{energy,j,t-1} \, x \, Post_t + \vartheta^h Post_t + \theta^h X_{j,t-1} + \varepsilon_{j,t+h} \; \forall \; h = 0, \, 1, \, 2, \ldots, 12 \quad (1)$$

The dependent variable is CPI inflation, $\pi^{CPI}_{j,t+h}$. α^h_j are country fixed effects. Controls $X_{j,t-1}$ include 4 lags of CPI inflation and of the output gap. The main coefficients of interest are the sequences of coefficients β^h, which capture the baseline passthrough of lagged energy price inflation, $\pi_{energy,j,t-1}$, into CPI inflation, and γ^h, which measures any change in the passthrough from energy prices into CPI inflation since Covid. The $Post_t$ dummy variable is defined to equal one for the years 2020 onward, and zero otherwise (for 2010-19).

As the literature highlights the importance of non-linear dynamics during 2020-24 and the extraordinary nature of some of the energy shocks (Online Annex Figure 2.2.2), we also estimate a version of specification (1) with non-linear quadratic and cubic terms (similar to Dao et al., 2024).

$$\pi^{CPI}_{j,t+h} = \alpha^h_j + \textstyle\sum_{k=1}^{3} \beta^h_k \, \pi^k_{e,j,t-1} + + \textstyle\sum_{k=1}^{3} \gamma^h_k \, \pi^k_{e,j,t-1} \, x \, Post_t + \vartheta^h Post_t + \theta^h X_{j,t-1} + \varepsilon_{j,t+h} \; \forall \; h \; 0,1,2,\ldots,12 \quad (2)$$

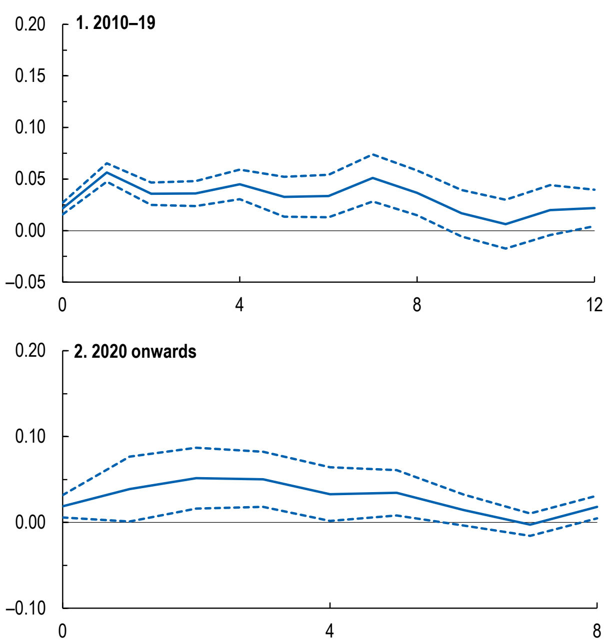
Online Annex Figure 2.2.4. Marginal Effects of Energy Price Inflation from a Non-linear Specification
(Percentage points)



Sources: Haver Analytics; IMF CPI database; and IMF staff calculations.
Note: Figure reports results of non-linear local projections of country-level CPI on energy price inflation for a 100bps energy inflation change, estimated on 2010–24 data. Graphs report local projection coefficients and 95% bands for three levels of energy inflation (1 percent, 11 percent - the pre-2020 standard deviation, 20 percent - the standard deviation including 2020–23). AEs = advanced economies; EMDEs = emerging market and developing economies. CPI = Consumer price index.

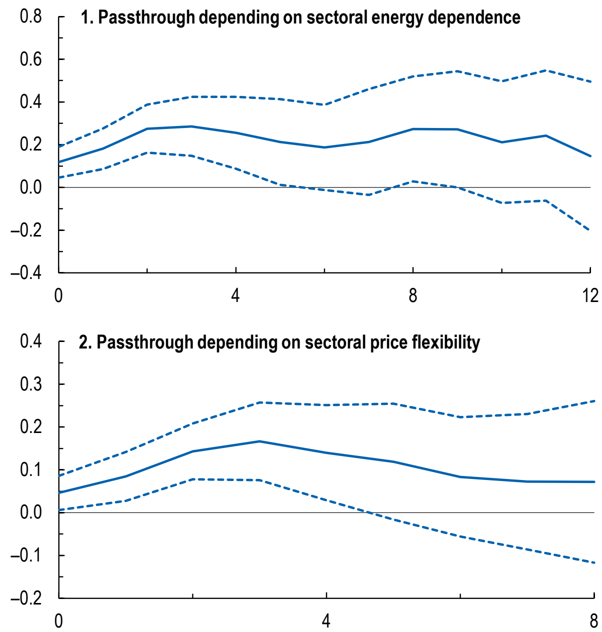
Now the marginal effects of energy prices onto CPI inflation also depend on the level of energy price inflation. Hence, we report the marginal effects for different levels of energy prices below. Online Annex Figure 2.2.4 finds no evidence for a systematic strengthening of the passthrough. The peak responses are slightly larger at higher levels of energy inflation, suggesting that non-linearities play a role. When energy inflation is 1 percent, a one percentage point increase in energy inflation leads to a peak rise in CPI inflation of about .05 percentage points in AEs. At 20 percent energy inflation, a one percentage point increase in energy inflation triggers about .08 percentage points of CPI inflation at the peak and the response is also more persistent.

Online Annex Figure 2.2.5. Pre and Post-Covid Energy Price Pass-through in AEs from IV Specification
(Percentage points)



Sources: Haver Analytics; IMF CPI database; and IMF staff calculations.
Note: Figure reports results for instrumental variable local projections estimation of country-level CPI on energy price inflation for a 100bps change in energy price inflation, estimated on 2010–24 sample for advanced economies. Instruments are oil pr~~ice shocks from Kaenzig (2021). Graphs report second~~ stage local projection coefficients along with 95 percent confidence bands.

Online Annex Figure 2.2.6. Sectoral Passthrough of Energy Inflation
(Percentage points)



Sources: Haver Analytics; Organisation for Economic Co-operation and Development; and IMF staff calculations.
Note: Figure reports results for local projection of sectoral inflation (measured as sectoral value-added deflators) on energy inflation for a 100 basis points energy inflation shock. Panel 1 reports local projection coefficients for double interaction of energy inflation and energy input share. Panel 2 reports coefficients for interaction of energy inflation and sectoral stickiness. Dashed lines are 95 percent confidence bands.

An additional concern with specification (1) is that energy inflation does not represent a fully exogenous shock, even if we used a lag of energy inflation to mitigate concerns about simultaneity bias. Hence, we estimate equation (1) as a local projections instrumental variables specification where we instrument energy inflation with the oil supply news shock constructed in Kaenzig (2021). Online Annex Figure 2.2.5 shows that the pre-Covid and post-Covid estimates for energy price passthrough are comparable for AEs.[1]

Finally, to investigate the sectoral patterns surrounding energy price passthrough, equation (3) tests whether the passthrough of

[1] In EMDEs, the first-stage F-stats are below the critical values to rule out weak instruments, hence we do not estimate the second stage LP-IV for EMDEs as instrumental variables regressions with weak instruments can lead to biased estimates.

energy prices is stronger in more energy-dependent sectors and in sectors with higher price flexibility – two key sectoral characteristics for the structural model. This estimation requires sector-level data. For each sector in the OECD international input-output tables, we compute a sector's energy dependence as the total direct (inputs purchased from the energy sector) and indirect (energy reliance of suppliers scaled by input share of supplier) energy share in total inputs.[2] Sectoral price flexibility, δ_i, is computed based on the sectoral price flexibility measures for the US from Rubbo (2023). We assume that sectoral price flexibility is the same for US and non-US sectors. Our specification is:

$$\pi_{i,j,t+h} = \alpha_{i,j}^{h} + \alpha_{j,t}^{h} + \beta^{h}\, \pi_{energy,j,t}\, x\, c_{i,j} + \epsilon_{i,j,t+h} \;\; \forall\, h = 0,1,2, \dots ,12 \tag{3}$$

where $c_{i,j}$ is a sectoral price characteristic that is either sectoral energy dependence, $s_{i,j}^{energy}$, or sectoral price flexibility, δ_i. Sector-country and country-time fixed effects absorb the impact of time-invariant heterogeneity and macroeconomic conditions.

Online Annex Figure 2.2.6 confirms that passthrough of energy inflation into sectoral inflation is stronger in sectors with higher energy dependence and with more flexible prices. Quantitatively, a sector with a 1 standard deviation (9 percentage point) higher energy dependence, has .027 percentage points higher sectoral inflation when energy inflation rises by 1 percentage point. This is quantitatively large as the average passthrough of energy inflation into CPI inflation is about .06 percentage points for 1 percentage point of energy inflation. In 2022Q1, energy price inflation in the US was 33.4 percent. Comparing the least to the most energy-dependent sector in the US economy, the most connected sectors is estimated to have had 2.71 percentage points higher sectoral inflation. Similarly, sectors with stickier prices have stronger energy price passthrough as evidenced in Figure A6, Panel 2. Going from the least (professional and scientific services) to the most price flexible sector (agriculture) when US energy inflation was 33.4 percent in 2022Q1 implies 3.4 percentage points higher sectoral inflation for the most price flexible sector.

Analytical Details on Phillips Curve Estimation

For the bivariate Phillips curve estimation, we run country-by-country regressions separately for the pre-Covid and post-Covid periods:

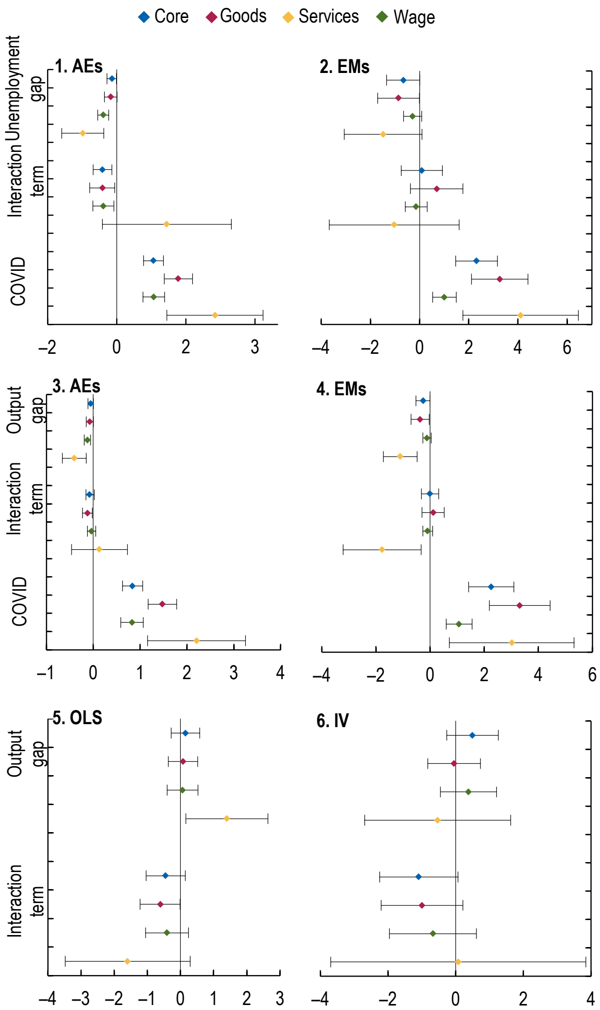
$$\pi_{i,t}^{s} = \alpha_i^{pre} + \beta_i^{pre}\hat{u}_{i,t} + \varepsilon_{i,t} \quad for\ t = 2010Q1, \dots, 2019Q4 \tag{4}$$

$$\pi_{i,t}^{s} = \alpha_i^{post} + \beta_i^{post}\hat{u}_{i,t} + \varepsilon_{i,t} \quad for\ t = 2020Q3, \dots, 2024Q1 \tag{5}$$

$\pi_{i,t}^{s}$ is inflation for $s \in \{core, goods, services, wages\}$. $\hat{u}_{i,t}$ is the unemployment gap estimated using a univariate HP-filter.

[2] To compute the indirect energy share we rely on the Leontief inverse; s Bartelme and Gorodnichenko (2015) and Miyomoto and Nguyen (2023) for more details on how to compute the total input share from input-output matrices.

Online Annex Figure 2.2.7. Estimates from Richer Phillips Curve Specification
(Coefficient)



Sources: Consensus Economics; Haver Analytics; and IMF staff calculations.
Note: Panel 1 and 2 report estimates from richer Phillips curve estimation following Equation (6) from 4 specifications with respectively core, goods, services, and wage inflation as dependent variables. For estimations with wage inflation, 2020 data are excluded. Panel 3 and 4 estimate the same 4 specifications with the output gap as a measure of slack. The output gap is multiplied by –1 to keep the coefficient signs comparable. Panel 5 and 6 implement an OLS and IV estimation within the Euro area with time fixed effects. Instruments are lagged economic slack and lagged inflation expectations. Interaction term captures the interaction of unemployment or output gap with the Covid dummy. AEs = advanced economies, EMs = emerging markets. OLS = ordinary least squares, IV = instrumental variables.

Figure 2.6, Panels 2 and 3 in the main chapter reports the cross-country distribution of the difference in the estimated slopes $\Delta_i^{\beta} = \beta_i^{post} - \beta_i^{pre}$ and intercepts $\Delta_i^{\alpha} = \alpha_i^{post} - \alpha_i^{pre}$ for different inflation measures. It shows that the Phillips curve has shifted and steepened near-universally around the globe. A number of studies emphasize theoretical mechanisms with a non-linear Phillips curve (e.g., Benigno and Eggertsson 2024, Harding et al. 2023). The presence of episodes with tight labor markets but low inflation in the pre-Covid era (Figure 2.6, Panel 1) appears to align more closely with the shifting and steepening pattern documented in the chapter. Other papers that show shifting and steepening include Gudmundsson et al. (2024), Inoue et al. (2023), and Smith et al. (2024).

The bivariate regressions are subject to two concerns. First, there could be omitted variables such as energy prices, inflation expectations, or lags of inflation. Second, inflation expectations and inflation may be simultaneously determined creating an endogeneity problem. Specification (6) adds a richer set of control variables similar to Gudmundsson et al. (2024) and we further consider an instrumental variables specification where we instrument inflation expectations and economic slack with their lags.

$$\pi_{i,t} = \alpha_i + \beta gap_{i,t} + \gamma Covid_t * gap_{i,t} + \delta Covid_t + \varphi \pi_{i,t}^{e} + \theta X_{i,t} + \varepsilon_{i,t} \qquad (6)$$

Controls include two lags of the inflation measures, lagged energy inflation, lagged import price inflation, and one-year ahead inflation expectations.[3] Estimates from equation (6) are reported in Online Annex Figure 2.2.7 (Panels 1 and 2) and are broadly consistent with the findings from

[3] Results are robust to using 5-year ahead inflation expectations instead.

Figure 2.6 in the main text. In particular, the shifting and steepening of the Phillips curve in AEs is confirmed and these patterns are again stronger for goods than for services.[4] In EMs, the patterns are weaker overall. While there is evidence for an upwards shift in the Phillips curve, there is no evidence for a steepening of the Phillips curve as the estimated coefficients are statistically insignificant and their magnitudes are close to zero for core, goods, and services inflation.[5]

In another robustness check, we re-estimate the pooled cross-country Phillips curve specification with the output gap as a measure of slack (Online Annex Figure 2.2.7, panels 3 and 4). To make coefficients comparable to the results with the unemployment gap, we multiply the output gap by minus one so that a more negative value indicates an economy with less slack. Qualitatively, the results from Figure 6 in the chapter are confirmed, again with a stronger shifting and steepening in AEs and more so for goods than for services inflation. The magnitudes in Online Annex Figure 2.2.7 (Panels 3 and 4) are smaller since the output gap has a larger standard deviation than the unemployment gap (2.05 percent vs. .91 percent in AEs; 2.50 percent vs. .99 percent in EMs).

Finally, some recent papers highlight the importance of regional data to identify the Phillips curve as cost push shocks in aggregate data may bias aggregate Phillips curve estimates downward by introducing a positive relationship between inflation and unemployment (Hooper et al, 2020; McLeay and Tenreyro, 2020; Hazell et al., 2023). These identification challenges are potentially compounded when monetary policy offsets demand shocks, which are the shocks needed for identification (McLeay and Tenreyro, 2020). While detailed regional data are not available for many of the countries in our large sample, we can estimate a specification for the Euro area, where monetary policy is set uniformly for all countries. Adding a time fixed effect to equation (6) absorbs the variation from Euro area wide supply shocks[6], thus mitigating concerns about our result being biased due to cost push shocks. The time fixed effect also removes any variation stemming from Euro area-wide monetary policy from the regression. OLS and IV results (Online Annex Figure 2.2.7, panels 5 and 6) are broadly consistent with our earlier estimates, suggesting a flat pre-Covid Phillips curve and a substantial steepening of the Phillips curve post-Covid.[7] The point estimates for the change in the slope are somewhat larger but so are the confidence bands around the estimate change in the slope.

Analytical Details on Inflation Decompositions

$$\pi_{i,t}^{h} = \mu_i + \theta\pi_{i,t}^{energy} + \varepsilon_{i,t} \tag{7}$$

$$\pi_{i,t}^{Core} - \pi_{i,t}^{e,\ LT} = \alpha_i + \beta slack_{i,t} + \gamma Covid_t * slack_{i,t} + \delta Covid_t + \phi(L)\pi_{i,t}^{h} + \theta(L)X_{i,t} + \varepsilon_{i,t} \tag{8}$$

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[4] The model in the main text provides an explanation for steepening of the Phillips curve while Gudmundsson et al. (2024) show how relative price shifts can lead to a shift in the Phillips curve intercept.

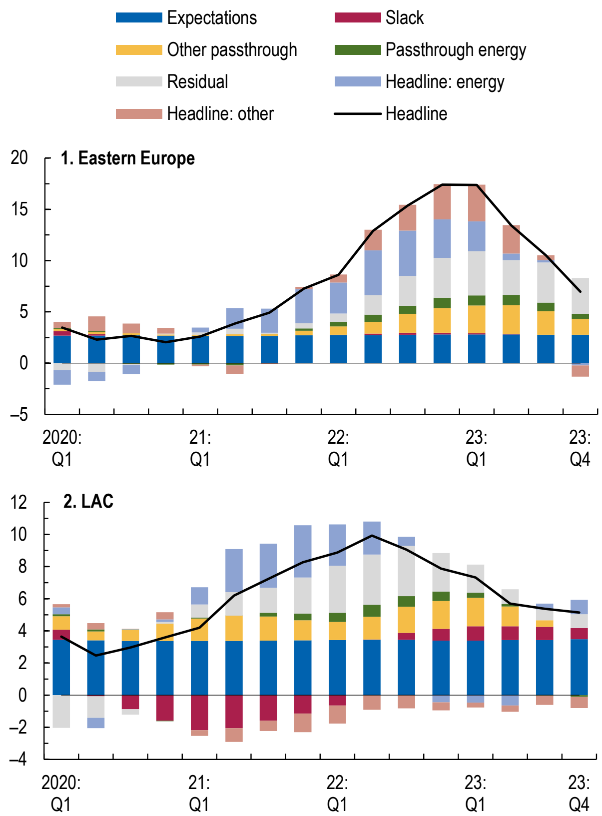
[5] In a further robustness check, we re-estimate equation (7) using an instrumental variables specification where we instrument inflation expectations and the unemployment gap with their lags. Result are comparable.

[6] We drop Croatia from the sample as they only joined the Eurozone in 2023.

[7] The shifting of the Phillips curve cannot be identified separately any more as the post-Covid change in the constant becomes co-linear with the time fixed effect.

The inflation decompositions proceed in two steps (similar to Dao et al., 2024). First, we construct "headline inflation shocks" as the difference between headline and core inflation. These headline inflation shocks are then regressed on energy inflation to identify an energy component – the fitted value from regression (7) – and a non-energy component, the residual from equation (7). In the second step, we estimate a Phillips curve specification in equation (8), with the deviation of core inflation from 5-year inflation expectations as the dependent variable. Otherwise, the specification in (8) is similar to equation (6) with economic slack, an interaction of slack with a Covid dummy, lagged inflation, import prices, and headline inflation shocks as regressors.[8] Throughout, we estimate equations (7) and (8) as pooled regressions for other AEs and, separately, for EMDEs, to maintain comparability with the earlier Phillips curve estimation.[9]

Online Annex Figure 2.2.8. Heterogeneity across Emerging Markets



Sources: Consensus Economics; Haver Analytics; and IMF staff calculations.
Note: Slack is measured using the unemployment gap (estimated via a univariate Hodrick–Prescott filter). Country-level contributions are aggregated using PPP GDP weights. Fitted values for inflation contributions are converted into 12-months rates. LAC includes Brazil, Chile, Colombia, and Mexico. Eastern Europe includes Bulgaria, Hungary, and Romania. LAC = Latin America and the Caribbean.

Core inflation is measured using the median inflation measure from Dao et al. (2024) where available, otherwise we use headline inflation excluding food and energy. Labor market tightness is measured using the vacancy-unemployment ratio (following the argument by Barnichon and Hale Shapiro, 2024) in AEs. For EMs, where timely vacancy-to-unemployment ratio data is scarce, we use the unemployment gap estimated using a univariate HP-filter. The decomposition in equations (7) and (8) allows for labor market tightness to affect core inflation directly – and not only indirectly through wage inflation as in the decompositions by Bernanke and Blanchard (2024).

[8] For AEs, import prices are primarily driven by energy prices with about ¾ of import prices explained by energy during the inflation surge of 2021-2022. Thus, the main contribution of import prices to inflation in AEs is through energy and we therefore exclude import prices from the AE specification.

[9] For the US, we estimate a monthly specification to ensure that we have a sufficient number of observations.

All charts with results from inflation decompositions in the main text and appendix convert the quarterly data[10] to 12-month moving averages.

Online Annex Figure 2.2.8 breaks down the main text result in Figure 2.7 by emerging market region. Inflation rose notably higher in Eastern European emerging markets, many of which were highly reliant on energy from Russia and thus particularly exposed to the energy price shocks following Russia's invasion of Ukraine. In fact, core inflation in Eastern European EMDEs only rose about 2 percentage points higher than core inflation in LAC. Yet, large headline inflation shocks, in particular to energy, led to headline inflation peaking at about 16 percentage points (measured as a 12-month moving average) in Eastern Europe, notably higher than in LAC where headline inflation peaked at around 10 percentage points. Notwithstanding large inflation movements, inflation expectations in both LAC and Eastern Europe remained stable with minimal movements. While real wage growth in Eastern Europe picked up in recent quarters; the passthrough into higher inflation has so far been limited as the unemployment gap has not tightened yet.

Further details on the comparison of historical inflation episodes

This section provides a full definition of inflation episodes and discusses further results. Following Ari et al. (2023), the following algorithm identifies the inflation episodes:

1. Select country-year pairs where average annual inflation rises by at least 2pp,

   i.e., $\Pi_T - \Pi_{T-1} \geq 2$ percent.
2. Drop episodes in low-income, non-market economies.
3. Drop episodes where post-shock inflation remains low, *i.e.,* $\Pi_T < 3$ percent.
4. Drop episodes where pre-shock inflation is too high,

   i.e., average$(\Pi_{T-1}, \Pi_{T-2}) > 25$ percent
5. Drop episodes where the inflation is a reversion to recent high inflation,

   i.e., $\max(\Pi_{T-2}, \Pi_{T-3}) > \Pi_T$

By extending the dataset of Ari et al. (2023) to include post-pandemic periods, we identify a total of over 200 inflation episodes.

Deviation from Taylor-rule-implied Tightening

To be able to further compare the monetary tightening in the recent episodes with those of the 1970s, we compare their deviations from the respective Taylor rule-implied policy reactions.

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[10] In an additional exercise, we estimate the same inflation decompositions using monthly data and running country-by-country specifications as in Dao et al. (2024). This relaxes the implicit assumption in equations (8) and (9) of common cross-country coefficients. The main findings are all confirmed.

Specifically, we calculate changes in policy rates from their pre-episode average levels and compare them to the implied tightening according to a standard Taylor rule.

To do so, we first propose the following unemployment-gap based Taylor rule formulation:

$$r_t^{TR} = r^* + \phi_\pi(\pi_t - \pi^*) - \phi_u(u_t - u^*)$$

We calibrate this rule following Hofmann and Bogdanova (2012), setting $\phi_\pi = 1.5$ and $\phi_Y = 1$. Then, using Okun's law, we set $\phi_u = 2\phi_Y$.

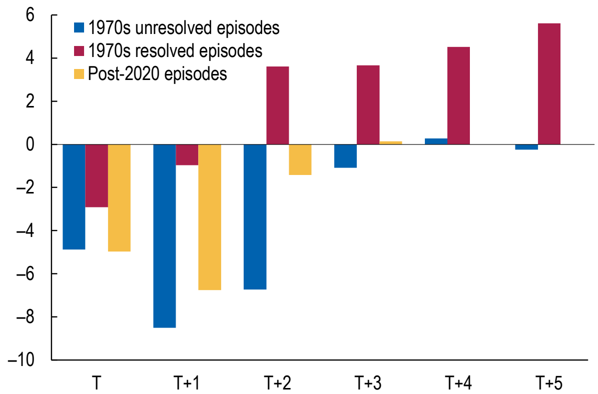
To calculate the Taylor-rule implied tightening between post-inflation-episode, *t*, and the average of the last two pre-inflation-episode years, we subtract the period *t* Taylor-rule from the average interest rate implied by the same Taylor rule:

$$r_t^{TR} - \left(\frac{r_{T-1}^{TR}+r_{T-2}^{TR}}{2}\right) = \phi_\pi\left(\pi_t - \left(\frac{\pi_{T-1}+\pi_{T-2}}{2}\right)\right) - \phi_u\left(u_t - \left(\frac{u_{T-1}+u_{T-2}}{2}\right)\right),$$

for *t* = {T, T+1, T+2, T+3, T+4, T+5}.

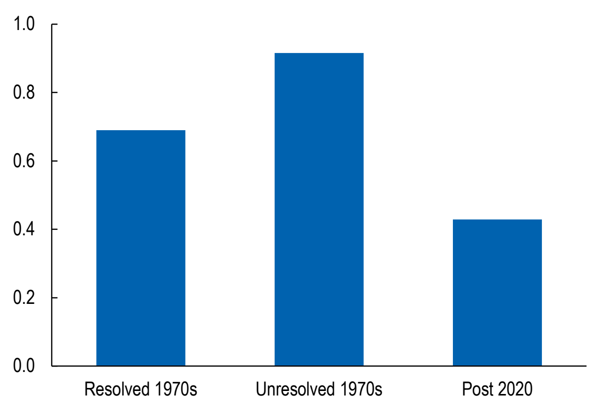
This formulation does not depend on the time invariant variables, such as the neutral rate and the natural rate of unemployment. Then, we take the differential of the observed short-term interest rate tightening from the Taylor-rule-implied tightening as follows:

Online Annex Figure 2.2.9. Deviation from Taylor-Rule-Implied Tightening
(Percent)



Sources: Haver Analytics; Ari and others(2023); and IMF staff calculations.
Note: 1970s unresolved includes 12 inflation shock episodes and 1970s resolved episodes include 13 inflation shock episodes (1973-1979). Post-2020 encompasses 125 inflation episodes centered around 2021 and 2022. Bars refer to percent deviation from Taylor-rule-implied tightening.

Online Annex Figure 2.2.10. Pre-Shock Inflation Volatility
(Variance normalized by its mean)



Sources: Ari and others (2023); Haver Analytics; and IMF staff calculations.
Note: 1970s unresolved includes 12 inflation shock episodes and 1970s resolved episodes include 13 inflation shock episodes (1973–79). Post-2020 encompasses 125 inflation episodes centered around 2021 and 2022. Bars refer to averaged pre-shock inflation volatility across inflation episodes, defined as the variance of inflation between t − 5 and t − 1 normalized by its mean over the same period.

$$\Delta \equiv \left(r_t^{pol} - \left(\frac{r_{T-1}^{pol} + r_{T-2}^{pol}}{2}\right)\right) - \left(r_t^{TR} - \left(\frac{r_{T-1}^{TR} + r_{T-2}^{TR}}{2}\right)\right)$$

Online Annex Figure 2.2.9 plots the differential for 1970s unresolved episodes, 1970s resolved episodes, and post-2020s. In line with Figure 2.9 in the main chapter, the post-2020 tightening with respect to Taylor-rule-implied tightening is in between resolved and unresolved inflation episodes of 1970s. For all three sets of episodes, the Taylor rule suggests a stronger tightening of policy rates during the first two years of the episodes relative to the data. This is likely due to the lagged response of policy to the shocks. Notably, the deviation between the actual policy rate changes and those suggested by the Taylor rule is smaller for resolved episodes and for the post-2020 period, than the unresolved episodes. In subsequent periods, policy rate changes in resolved episodes of 1970s became more pronounced than what the Taylor rule would suggest in most cases, likely in an effort to anchor inflation expectations.

Online Annex Figure 2.2.10 examines inflation volatility prior to the inflation episodes to gauge the degree of inflation expectations anchoring as inflation expectations are likely to be better anchored if inflation has been more stable historically. We resort to this imperfect proxy, given the limited availability of historical inflation expectations data. This analysis shows that volatility in periods preceding post-2020 inflation was significantly lower compared to the 1970s.

Online Annex 2.3. Monetary policy transmission: VAR Analysis

This online annex describes the approach used to analyze empirically the transmission of monetary policy tightening cycles.

Methodology

Models and data. Country-specific small-scale structural VARs with time-varying parameters and stochastic volatility are estimated for selected AEs (US, euro area, and the UK) and EMs (India, Brazil, and Mexico). Each model includes five variables: real GDP, consumer prices, short-term policy rates and two more variables capturing specific channels of transmission.[11] In the baseline specification the latter two include long-term interest rates (i.e., the 10-year sovereign bond yield) and the unemployment rate for AEs and the terms of trade and the nominal effective exchange rate for the EMs.[12] For AEs, a shadow rate estimate is used as proxy for the short-term policy rate, to account for the adoption of non-standard monetary policy measures when the effective lower bound in official policy rates was approached.[13] The model is estimated with quarterly data for the longest available sample for each country (starting with 1960Q1 onwards for the United States and United Kingdom, 1970Q1 for the euro area, and 1997Q1 for India, Brazil and Mexico) covering through 2024Q2, using standard Bayesian techniques following Primiceri (2005), Del Negro and Primiceri (2015) and Gambetti and Musso (2017). To ensure stationarity of each variable, real GDP and consumer prices are expressed as

[11] For the US, the reference consumer price index used is the Personal Consumption Expenditures Chain-type Price Index, but results are very similar if the CPI (Consumer Price Index for All Urban Consumers) is used.

[12] All data are from the WEO database, unless otherwise specified. The terms of trade indices for India, Brazil and Mexico are from Haver.

[13] For the US the reference policy rate is the effective federal funds rate, replaced by the Wu-Xia shadow rate estimate during the quarters in the 2009-2015 and 202-2021 periods when the latter is negative. For the euro area, the reference policy rate is €str from end-2019 onwards, linked back with the Eonia to 1999 and the 3-month Euribor to 1970, replaced by the Wu-Xia shadow rate estimate during the quarters in the 2011-2022 period when the latter is negative. For the UK the reference policy rate is the official bank rate, replaced by the Wu-Xia shadow rate estimate during the quarters in the 2009-2019 period when the latter is negative. For details of the approach used to estimate shadow rates see Wu and Xia (2016) and Wu and Xia (2020). The source of the Wu-Xia shadow rate estimates is Haver.

annualized q-on-q growth rates, while interest rates, unemployment rates, the terms of trade indices and the NEER are expressed as first difference.

Online Annex Table 2.3.1. Identification Restrictions

Variable; Shock	Aggregate Supply	Aggregate Demand	Monetary Policy
Real GDP Growth	-	-	-
Consumer Price Inflation	+	-	-
Short-term Policy Interest Rate		-	+
AEs: 10Y Gov. Bond Yield; EMs: ToT Index			
AEs: Unemployment Rate; EMs: NEER			

Source: IMF staff calculations.
Note: A "-" ("+") signals that the impulse response of the corresponding variable to the corresponding shock is negative (positive) on impact and for the following three quarters. Entries left blank signal that no restriction is imposed. The fourth and fifth variables are the ten-year government bond yield (10Y Gov. Bond Yield) and the unemployment rate for advanced economies (AEs) and the terms-of-trade (ToT) index and the nominal effective exchange rate (NEER) for emerging economies (EMs), respectively.

Identification. Standard sign restrictions are imposed for four quarters for identification of monetary policy shocks, aggregate supply shocks and aggregate demand shocks (Online Annex Table 2.3.1).

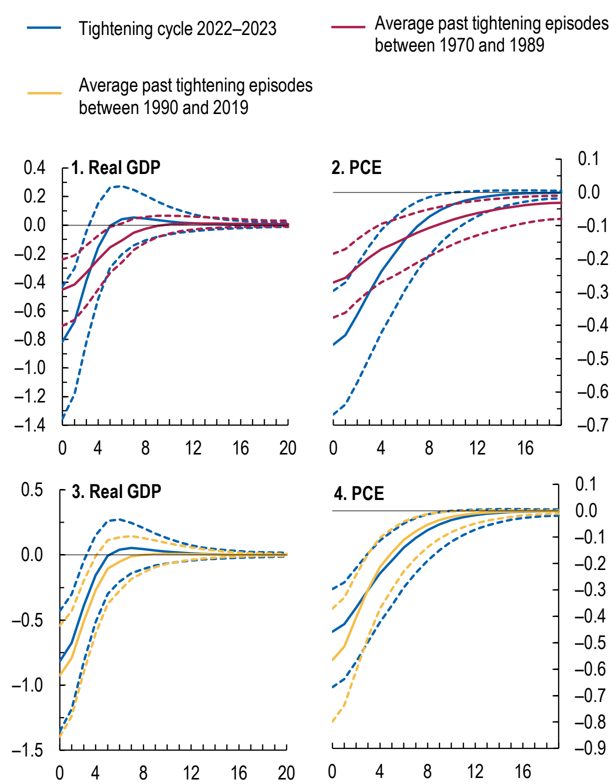
Online Annex Table 2.3.2. Dates of the Most Recent Tightening Cycles

Country/Region	First Increase	Last Increase	First Cut
US	Mar-22 (FFR: 0.25% → 0.50%)	Jul-23 (FFR: 5.25% → 5.50%)	Sep-24 (FFR: 5.50% → 5.00%)
Euro area	Jul-22 (DFR: –0.50% → 0.00%) (MRO: 0.00% → 0.50%) (MLF: 0.25% → 0.75%)	Sep-23 (DFR: 3.75% → 4.00%) (MRO: 4.25% → 4.50%) (MLF: 4.50% → 4.75%)	Jun-24 (DFR: 4.00% → 3.75%) (MRO: 4.50% → 4.25%) (MLF: 4.75% → 4.50%)
UK	Dec-21 (Base rate: 0.10% → 0.25%)	Aug-23 (Base rate: 5.00% → 5.25%)	Aug-24 (Base rate: 5.25% → 5.00%)
India	May-22 (Repo rate: 4.00% → 4.40%)	Feb-23 (Repo rate: 6.25% → 6.50%)	
Brazil	Mar-21 (Selic rate: 2.00% → 2.75%)	Aug-22 (Selic rate: 13.25% → 13.75%)	Aug-23 (Selic rate: 13.75% →13.25%)
Mexico	Jun-21 (Cash rate: 4.00% → 4.25%)	Mar-23 (Cash rate: 11.00% → 11.25%)	Mar-24 (Cash rate: 11.25% → 11.00%)

Source: IMF staff calculations.
Note: FFR = Federal funds rate; DFR = deposit facility rate; MRO = main refinancing operations rate; MLR = marginal lending facility ra

Transmission. The transmission is measures using the estimates of the impulse response functions of output and consumer prices (both in levels) to a standardized contractionary monetary policy shock (with the peak response of the policy rate normalized to correspond to an increase by 100 basis points). This is accomplished by deriving responses as a function of the average values of the parameters estimated during each tightening period. These tightening periods are set based on the chronology provided by Blinder (2023) for the US and by delimiting the periods during which the policy rate increased for at least two quarters in other countries (Online Annex Table 2.3.2).

Online Annex Figure 2.3.1. Responses of Output and Consumer Prices during Tightening Episodes in the United States



Source: IMF staff calculations.
Note: The *x*-axis represents number of quarters after the shock. Impulse response functions of real GDP and the personal consumption expenditures chain-type price index (PCE) for the US to a normalized monetary policy contractionary shock with an immediate impact of 100 basis points over tightening episodes. Blue lines are responses in the most recent episode, red and yellow lines are average responses during the historical episodes considered. Solid lines are the medians and dashed lines delimit the 68 percent highest posterior density set.

Output and Additional Results

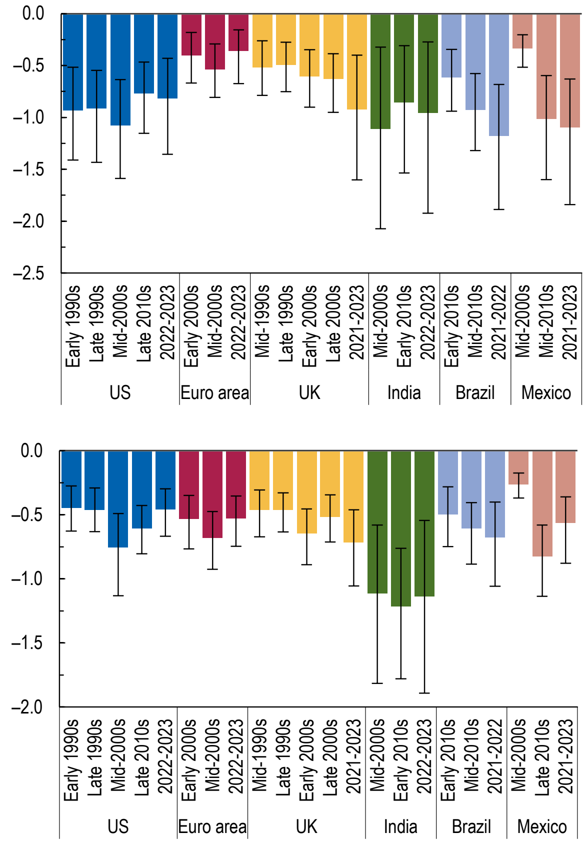
Online Annex Figure 2.3.1. plots estimated impulse responses to the normalized monetary policy tightening shock for the US, comparing the transmission to output and consumer prices of the latest rate hike (2022Q1-2023Q3) to the average for the tightening episodes during the 1970s and 1980s (five episodes: 1972Q1-1974Q3, 1977Q1-1980Q2, 1980Q3-1981Q1, 1983Q1-1984Q3, and 1988Q1-1989Q2) – see upper panels - and to the average for the tightening episodes between 1990 and 2019 (four episodes: 1993Q4-1995Q2, 1999Q1-2000Q3, 2004Q2-2006Q3 and 2015Q4-2019Q1) – see lower panels. In each case, the black lines represent the responses in the most recent episode, while the red lines are the average responses during the historical episodes considered (solid line is the median and dashed lines delimit the 68 percent Highest Posterior Density, or HPD, set).

Overall, while there are some changes across episodes, the differences are minor when assessing the whole profile of average responses over decades. The responses of output and consumer prices during the latest tightening cycle appear to be stronger in the short-term than those of the 1970s and 1980s but the responses during 1970s-80s seem to be statistically significant for longer. By contrast, the responses to the latest tightening episode are similar to those estimated on average during 1990-2019. Looking at the cumulative responses (i.e., the quarterly sum of the median impact over the quarters when the responses are significantly different from zero statistically), the transmission to output and consumer prices of the latest tightening cycle appears similar to the historical average.

Online Annex Figure 2.3.2. compares the transmission of the standardized monetary policy tightening shock over time for each country during tightening cycles since 1990, when all the jurisdictions considered had adopted de jure or de facto inflation targeting. The figure reports estimates of the peak impact of output and consumer prices, but the assessment of the transmission is similar when looking at the whole profile of the impulse responses.

Overall, there is some variation over time for each country in the transmission of tightening.[14] However, there is no strong evidence pointing to a systematic and significant difference in the magnitude of these responses for each country when comparing the latest episode to the average transmission observed between the 1990s and 2019.

Online Annex Figure 2.3.2. Peak Responses of Real GDP and Consumer Prices



Source: IMF staff calculations.
Note: Panel 1 shows peak responses of real GDP and panel 2 shows peak responses of consumer prices. The bars denote the country median peak responses, and the markers represent the upper and lower bounds of the 68 percent highest posterior density set of responses to a normalized monetary policy tightening shock with an immediate increase by 100 basis points of the short-term policy rate.

Online Annex 2.4. Further details on the Global Dynamic Network Model

Description

We develop an 11-sector, 2-country model and calibrate to the U.S. and the rest of the world using production network data from the OECD's ICIO tables.[15] Production in each sector is comprised of 3 factors: capital which is assumed to be fixed in the model, labor which can vary, and an intermediate bundle. These factors are combined using a constant elasticity of substitution (CES) production function with an elasticity of 0.5. The intermediate bundle is itself comprised of products from all 11 sectors in the economy with a CES

[14] Estimates are quantitatively similar to those of the empirical literature. For instance, Ramey (2016) reviews ten studies for the US and reports that the median peak impact of a normalized 100 basis points monetary policy shock to output is -1.6 percent (with interquartile range between -0.7 percent and -2.1 percent), which compares to an average peak response of -0.9 percent in our estimates for the US since 1990. Our conclusions are also qualitatively similar to those of available studies for specific countries. For instance, Barrett and Platzer (2024) find evidence that the transmission of the latest tightening shock in the US, beyond the very short run, was broadly in line with historical pre-pandemic averages. Similarly, Lane (2024) finds no significant evidence of changes in the transmission in the euro area.

[15] The 11 sectors are: Agriculture, Mining and Energy, Manufacturing, Construction, Wholesale & retail, IT & Telecommunications, Finance and Insurance, Real Estate, Professional, Scientific & Technical, Education, Health & Government Services, and Arts, Entertainment & Recreation.

production function with an elasticity of 0.1.[16] This low elasticity captures the difficulty in substituting between different *types* of goods in production (i.e., it is difficult to replace energy with manufactured goods in production). Finally, each sectoral type is a bundle comprised of a U.S. variety and the rest of the world variety. These are assumed to be substitutes with an elasticity of 1.5. Household consumption is similar in that there is a 2-nest CES production structure, where firstly different types of sectoral goods are combined into a bundle with an elasticity of 0.8. And each sectoral good is comprised of a U.S. variety and foreign variety combined with an elasticity of 1.5.

Prices in each sector adjust sluggishly as in Calvo (1983), where the degree of sluggishness varies by sector.[17] Slow price adjustment forces firms to absorb some of the cost changes into their margins and leaves their prices somewhat disconnected from costs of production. It also magnifies the effects of demand shocks on production and real GDP.

Relative demand for each sector varies endogenously as relative prices change and exogenously based on household taste shocks for different types of goods over others. We then follow Baqaee and Farhi (2022), Çakmaklı, Demiralp, Kalemli-Özcan, Yeşiltaş and Yıldırım (2021), Gourinchas, Kalemli-Özcan, Penciakova and Sander (2021) and others by modelling supply constraints in terms of an exogenous time-varying maximum workforce limit imposed on firms. These maximum limits are assumed to rarely bind in normal times allowing firms to choose their workforce size based on worker marginal products and the prevailing sectoral wage. In crisis times, these constraints may shift, or if demand is sufficiently high, they may bind. When they bind, firms' labor demand at the prevailing wage is curtailed to be consistent with the employment limit. This constraint effectively *lowers* their labor demand relative to the case without any employment limits.

The model also features two types of households: Ricardian households who can access financial markets and consume with exogenous consumption habits; and hand-to-mouth households who consume their labor income. The Ricardian households are Blanchard (1985)-Yaari (1965) style overlapping generations, have Greenwood–Hercowitz–Huffman (1988) preferences over consumption and leisure and habit formation. Aggregate wages are sticky and then labor supply is differentiated by sector with a constant elasticity of transformation of 0.76. This allows sectoral wages to vary somewhat with sector-specific shocks while aggregate wages remain sticky.

Finally, we assume that sectoral inflations expectations in the model deviate from rational expectations based on the following equation:

$$\pi^{e}_{s,t,t+1} = \rho_e \pi^{e}_{s,t-1,t} + \rho_l \pi_{s,,t-1} + (1 - \rho_e - \rho_l) E_t \pi_{\{s,t+1\}}$$

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[16] Production in one sector often will source some share of their intermediates from other firms in the same sector.

17 We obtain the Phillips Curve slopes from Rubbo (2023) and they are originally from Pasten, Schoenle and Weber (2020).

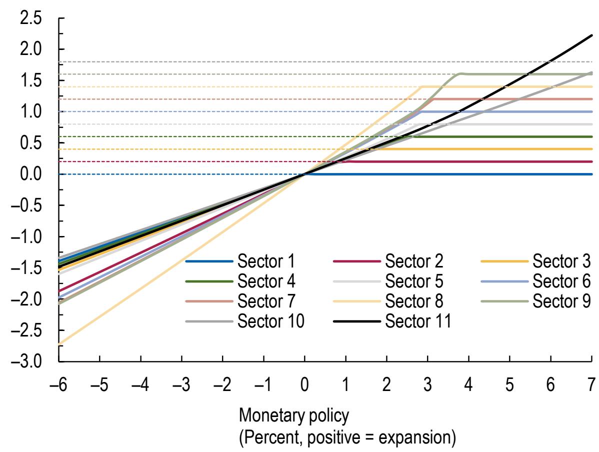
Where $\pi_{s,,t}$ is inflation in sector *s* at time *t* $\pi^{e}_{s,t,t+1}$ is inflation expectations in sector *s* formed at *t* for the period *t+1* and $E_t\pi_{\{s,t+1\}}$ are the model-consistent rational expectations formed in period *t* for inflation in sector *s* at time *t*. These expectations enter all our Phillips Curve equations when firms set prices. In all other cases where agents in the model form expectations (e.g. households, financial markets, etc), we assume expectations are formed in a model-consistent manner.

Further details on the non-linear Phillips Curve

Online Annex Figure 2.4.1. shows the sectoral supply constraints we imposed to deliver the non-linear Phillips Curve in Figure 2.11. For illustrative purposes, supply constraints were imposed arbitrarily in an ascending fashion in each of the 11 sectors. These are shown by the horizontal lines corresponding to the maximum level of employment (y-axis) allowed in that sector. Then monetary policy shocks of various sizes were imposed in a variety of scenarios and the employment effects of this are plotted in solid lines. The x-axis shows the size of the initial monetary policy shocks imposed.

Online Annex Figure 2.4.1. Sectoral Bottlenecks and Phillips Curves

(Percent, labor response to monetary shocks with constraints)



Source: IMF staff calculations.
Note: Horizontal dotted lines represent (arbitrarily ascending) maximum labor limits for each sector. The solid lines on the same panel show actual labor when we vary the level of aggregate demand using monetary policy. *X*-axis denotes monetary policy (positive = expansion), *y*-axis denotes change in labor.

When demand is low (negative or contractionary monetary policy shocks), employment in every sector is below their maximum levels and sensitive to small changes in demand. When demand is higher however, some sectors hit their supply constraints and employment cannot increase. If demand continues to rise in these sectors, prices must rise instead. This leads to higher inflation and less output for a given increase in demand and makes the aggregate Phillips curve steeper.

Shock Extraction

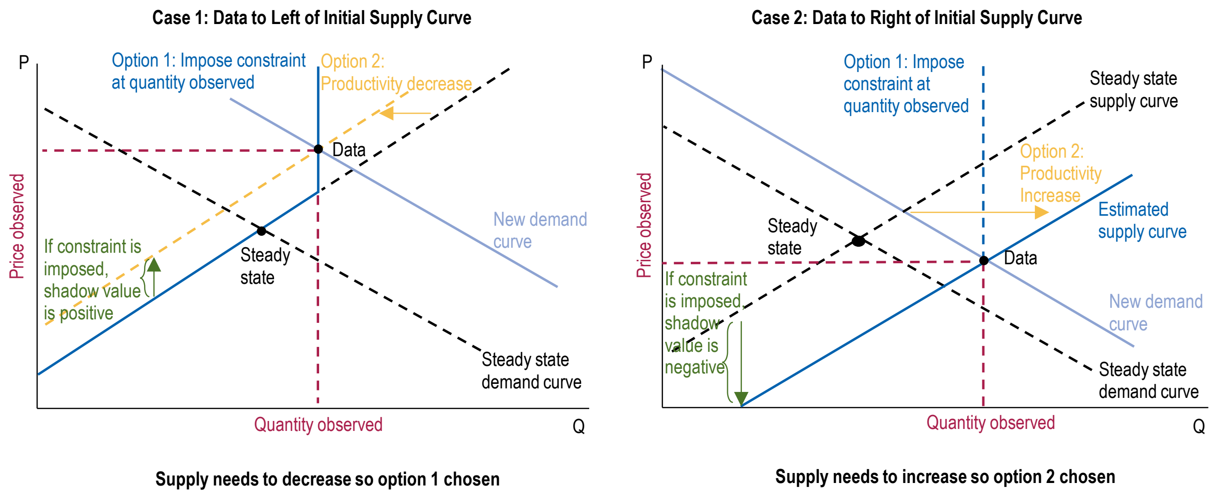
Our counterfactuals, which include earlier or later tightening, first require a model scenario that replicates the data for 2020Q1-2023Q4. This involves estimating the model-implied shocks that, when put together, exactly match the data.

Data was collected on sectoral value added, sectoral value-added deflators, import prices, aggregate CPI inflation, and interest rates for both the US and rest of the world. These were obtained from the Federal Reserve Economic Data, the OECD and Eurostat.

A quasi-non-linear shock estimation methodology is applied whereby first the model is linearized and then a set of shocks consistent with the observed data are estimated using the

Kalman filter in a manner that is always just-identified.[18] The identification of labor constraints relies on the assumption that negative supply shocks are due to labor constraints binding, while positive supply shocks are due to increases in labor productivity.

Online Annex Figure 2.4.2. Stylized Example of Constraint and Productivity Estimation



Source: IMF staff compilation.

To estimate the non-linear labor constraints, we define a "labor wedge" between the marginal product of labor and the prevailing market wage in each sector which is estimated using the smoother. Effectively, this represents the shadow price of the labor constraint and treated as an exogenous shock, which in turn identifies the level of the labor constraint.

The identifying assumption is that (i) labor productivity shocks must be positive and the labor wedge zero; or (ii) the labor wedge is positive and labor productivity shocks are zero. We do not allow *both* positive labor wedges and positive productivity shocks in the same period and in the same sector. If the resulting estimated shocks violate these assumptions, the active shock (either labor wedge or productivity) is switched and the Kalman filter re-run with the new set of shocks. This procedure is iterated to convergence.

We show a visual example of this approach in Online Annex Figure 2.4.2.. Each panel shows a hypothetical situation in the output market where the black dotted lines show the steady state supply and demand curves with the intersection denoting steady state price (vertical) and quantity (horizontal).

We go through two examples where we observe both the output price and quantity in this market.[19] In the first case (left panel), we observe data (a combination of price and quantity) to the left of the initial supply curve. To explain this observation demand needs to shift (in this case

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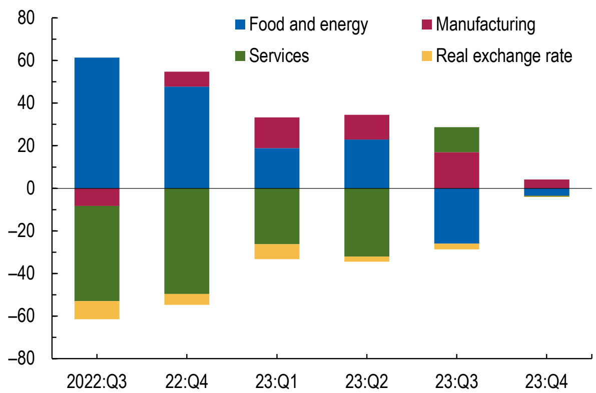
[18] The number of shocks matches the number of observables and the Kalman filter is conditioned so impact of initial conditions is small.

[19] One simplification in this diagram is that we work with data on *value added* rather than *gross output*. For the purposes of exposition, we label the horizontal axis "quantity" and ignore these distinctions.

up) but also supply needs to decrease.[20] Supply can decrease for 2 reasons: there was a supply constraint imposed where quantity cannot exceed the level observed or productivity decreased. The first is shown by the blue line with an estimated "shadow value" of the constraint given by the green line. The second case is shown in orange. With the data available it is not possible to separately identify a labor wedge increase from a productivity decrease which leads to the following identification assumptions being imposed:

1. Productivity shocks during this period are never negative.
2. Productivity shocks are zero whenever labor wedges are positive.

Online Annex Figure 2.4.3. Decomposition of the Total Effect of Sectoral Prices When the Rest of the World Tightens Later
(Percent, excess contribution)



Source: IMF staff calculations.
Note: This graph shows the excess total (direct and indirect) contribution of sectoral prices to the change in consumer price index (CPI) in the counterfactual where the rest of the world tightens three quarters later. It is computed by decomposing CPI changes into the contributions from changes in sectoral value-added deflators/costs and sector-specific expectations using the full set of Input-output linkages. When doing this decomposition, the real exchange rate affects the prices of foreign goods in all sectors and this contribution is shown with a separate bar. The excess contribution is calculated by subtracting the observed indirect effect from the indirect contribution of each sector assuming equal deflator rises in all sectors. Because this is an excess contribution, the bars sum to zero (i.e. there is no excess contribution in total).

Because the identification does not allow productivity to decrease, the procedure will assume that all of the required decrease in supply is driven by the imposition of a supply bottleneck and productivity will be assumed to be unchanged in this sector and period. Note that in the example here, a constraint has been imposed that is *above* the steady state level of output. That is, the price and quantity data suggest supply is constrained in a particular sector even though quantity observed has increased. This occurs because the observed price is above the level consistent with demand at that quantity**.**

The right panel shows a second case where the observed data is to the right of the steady state supply curve. In this case there are the same two options to explain the increase in supply: we could impose a constraint at the observed data or allow for a productivity shock to shift the supply curve right. However, in this case, any constraints imposed would have a negative "shadow value" of the labor wedge which is inconsistent with the notion of a *maximum* limit to labor.[21] Therefore, this data realization would be fully explained by a positive productivity shock.

In the counterfactual scenarios, wherever the labor wedge is positive, the corresponding level of labor is imposed as an occasionally binding constraint.

[20] Demand increasing is coincidental to this example. We could construct a similar case to the left of the steady state supply curve where demand falls.

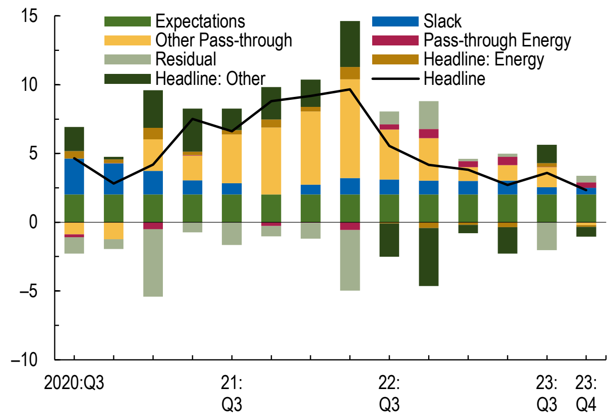
[21] A negative labor wedge is equivalent to *minimum* employment constraint which, if binding, would require firms to hire *more* workers than they would like to at the prevailing wage.

How counterfactuals are computed

In each counterfactual scenario, the Kalman filter is reused but with adjustments to the observables based on the scenario under consideration. For example, in the tightening earlier scenario (red line in Figure 2.13), the interest rate is adjusted to match the assumed earlier tightening. Labor wedges are then re-estimated given the new interest rate profile, keeping quantity of labor the same as in the baseline estimation. These re-estimated labor wedges can in principle be negative. In such cases, the wedge is set to zero and quantity of labor is re-estimated, until there are no more negative labor wedges.

Two exceptions to this procedure arise when computing the dotted lines in Figure 13. These dotted lines are intended to showcase the effect of treating the observed positive labor wedges as indicative of quantity restrictions on labor. To do so, the labor wedges in these lines are treated as typical shocks whose values are exogenously given and do not react endogenously to other shocks or fluctuations in the economy. Concretely, when treating a positive labor wedge as indicative of a labor constraint, a counterfactual with positive demand shocks would not raise the quantity of labor in that sector -- instead the value of the labor wedge would be increased to maintain labor at the quantity estimated to fit the data. By contrast, when the labor wedge is treated as a typical shock, the quantity of labor in that sector would rise in any counterfactual with a positive demand shock, while the labor *wedge* would remain at the same value estimated to fit the data. These counterfactuals are run assuming that the values of the labor wedges estimated in the shock extraction are observables.

Online Annex Figure 2.4.4. Inflation Drivers in the United States from Model Data
(Percent, year-over-year)



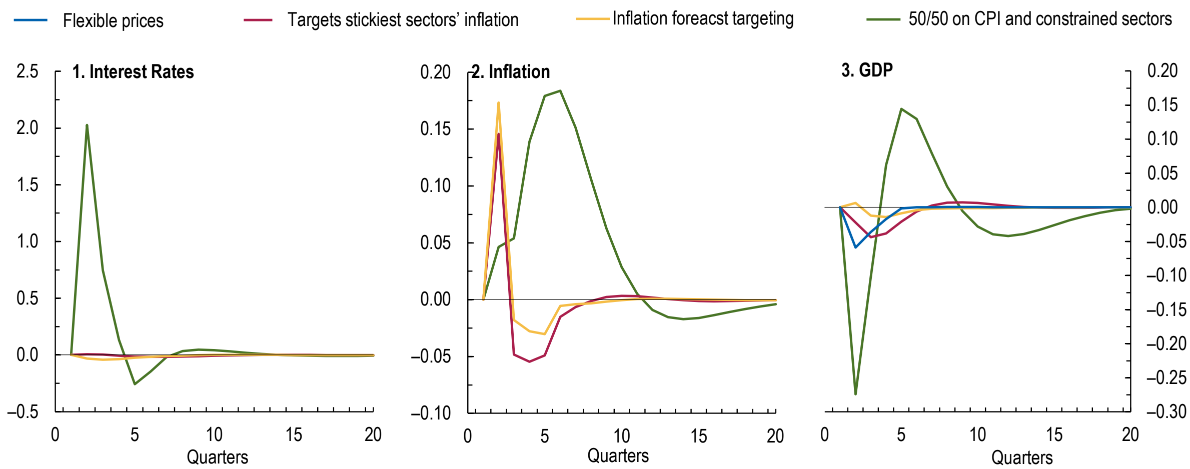
Sources: Federal Reserve Economic Data; Organisation for Economic Co-operation and Development; Eurostat; and IMF staff calculations.
Note: US inflation drivers are estimated following Dao and others (2024) with the parameters values estimated from a simulation of 1000 periods of boot strapped shocks that replicate to 2020:Q1 to 2023:Q4 sample. Five year ahead inflation expectations are assumed at steady state and slack is the deviation of GDP from steady state.

Details on alternative monetary policy scenarios

Online Annex Figure 2.4.5. below plots impulse response functions to shed light on the contribution of supply constraints to inflation and the analysis of the effects of different monetary policy strategies. To do so, the figure shows the effects of imposing capacity constraints on the labor markets in the agriculture, mining, and energy sectors without any changes in aggregate demand, so that the interaction effect of the constraint and demand is absent.

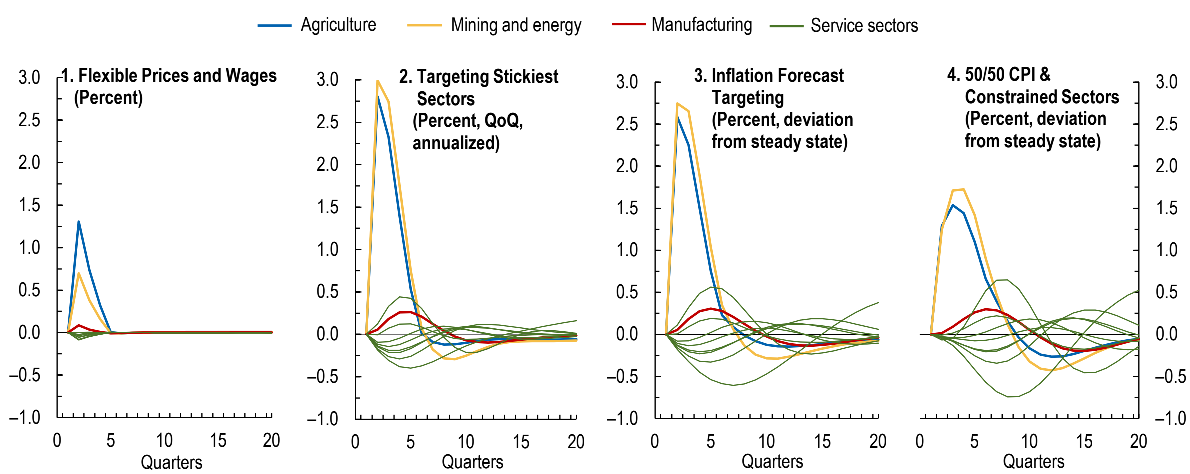
The key takeaway is that inflation rises for only one period and then moderates slowly.[22] This is because price rises are needed to maintain a labor constraint at a certain level, leading to a temporary surge in inflation in that sector, but to maintain the labor constraint at that level, no further price rises are needed – merely that the price *level* remains elevated. This suggests that

Online Annex Figure 2.4.5. Effect of Negative Capacity Constraint
(Percent deviation from steady state, quarter-over-quarter, annualized)



Source: IMF staff calculations.
Note: Scenario is a negative labor constraint shock in the agriculture, mining, and energy sectors. The Taylor rules are identical except for the inflation measure targeted. 'Targets stickiest sectors' inflation' targets the five sector with the steepest Phillips curves. 'Inflation forecast targeting' targets the four-quarter moving average of future CPI inflation. 'Flexible prices' shows relative prices in a scenario without nominal rigidities in any sector market. '50/50 CPI and constrained sectors' targets CPI inflation and sectoral inflation in agriculture, mining, and energy. In each case the Taylor parameter is 3 and the persistence parameter is 0.5 and neither GDP nor the output gap are targeted.

Online Annex Figure 2.4.6. Sectoral Price Dispersion
(Percent, sectoral prices relative to CPI)



Source: IMF staff calculations.
Note: Scenario is the same as in Figure 2.15. In all cases, the overall Taylor parameter on inflation is 3 with policy inertia of 0.5. Other rules are the same as Figure 2.15. CPI = Consumer Price Index; QoQ = quarter over quarter.

[22] Similar to Figure 18 in the main chapter, the policy rule targeting food and energy prices creates persistent inflation, in face of capacity constraint shocks only. This is because sectoral inflations of sticky price sectors, which are targeted less, have more persistence than those of flexible price sectors, which are targeted more. See the discussion of Online Annex Figure 2.4.6. for more details.

movements in constraints without changes in demand in that sector have highly transitory impacts on inflation.

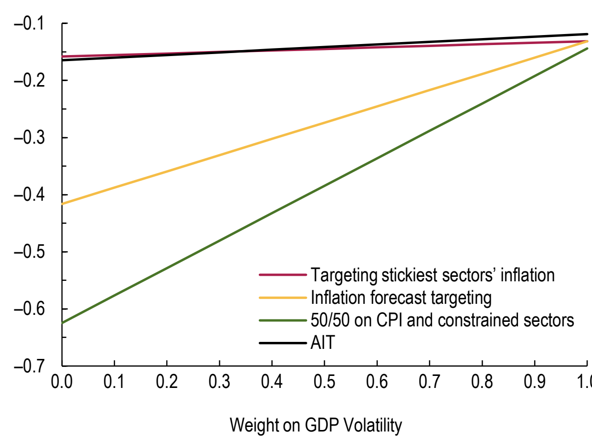
Online Annex Figure 2.4.6. shows how relative prices respond under different policy rules compared to the flexible price benchmark. When all prices are flexible in the first panel, agriculture, mining, and energy sectors which faces supply constraints have short-lived price increase, while prices of other sectors move marginally. The next two panels show that relative prices deviate from flexible price benchmark, especially for service sectors which tend to have stickier prices than goods sectors. The initial price dispersion under flexible prices is lower because sectors downstream of the shocked sectors are also able to pass on the higher costs, reducing dispersion from the average price level. Conversely, under sticky prices, the more flexible upstream sectors are able to quickly raise prices but sticky downstream sector are not, raising initial price dispersion.

In the final panel, when the policy rule aims to stabilize short-run inflation by targeting agriculture and energy sectoral inflation, the initial relative price movements of these sectors are close to the flexible price benchmark, but inflation momentum in other sectors builds overtime, which the policy rule does not respond to as strongly because inflation in the targeted upstream sectors is low or negative. This creates cyclical dynamics and larger gyrations with resource misallocation across sectors, as in Figure 2.15 in the main chapter.

Online Annex Figure 2.4.7. compares the volatility of CPI and GDP responses under four monetary policy rules in Figure 2.15, including AIT. Each line represents a linear combination of CPI and GDP volatilities with opposite signs. For instance, when the weight on GDP volatility is zero, the y-intercept of each line corresponds to the negative sum of squared deviations of CPI from its steady state. A higher line indicates lower volatility in either CPI or GDP, thereby suggesting that the corresponding rule is more effective at stabilizing the economy.

Online Annex Figure 2.4.7. Comparison of Policy Rules

(Weighted average of CPI and GDP volatilities)



Source: IMF staff calculations.
Note: The rules are the same as Figure 2.15. CPI = Consumer Price Index; AIT = Average Inflation Targeting.

As discussed in Figure 2.15, targeting the inflation of the stickiest sectors delivers the most effective strategy for CPI stabilization. The volatilities observed under this approach are quantitatively similar to those under AIT, with AIT slightly outperforming as the weight on GDP volatility increases. These rules clearly surpass the other two, when the rule targets forecasted inflation or puts weight on constrained sectors.

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