Annex

This appendix to Chapter 2 of the October 2021 World Economic Outlook provides documentation of data sources, country coverage, methodologies, and extensions of the analyses and narratives of the chapter. Section 2.1 compiles table summaries of the data sources and country coverage. Section 2.2 provides more details on the reduced form and structural Phillips Curve estimation. Section 2.3 elaborates on the analysis of inflation scares and market-based expectations. Section 2.4 illustrates a case study of the semiconductors sectors and its impact on inflation in the US, before moving on to the discussion of the quantile VAR analysis.

Annex 2.1 Countries and Data Sources

Annex Table 2.1.1 itemizes the data sources for the empirical exercises and Annex Table 2.1.2 lists the countries included in the different sections of the analyses.

Annex Table 2.1.1 Data Sources

Analysis	Indicator	Sources
Phillip's Curve	Bilateral Exchange Rate against the US dollar	IMF, Directions of Trade Statistics
	Bilateral Exports and Imports	IMF, Directions of Trade Statistics
	Core Consumer Price Index	Haver Analytics
	Domestic Output Gap	IMF, World Economic Outlook Database, and IMF staff calculations
	Producer Price Index	Haver Analytics
	External Price Pressure	IMF staff calculations
	Foreign Output Gap	IMF staff calculations
	Nominal Effective Exchange Rate	IMF staff calculations
	Nominal Imports, Exports, and GDP	IMF, World Economic Outlook Database
	Unemployment	IMF, World Economic Outlook Database
Inflation Expectations Anchoring	5-year 5-year forward breakeven rate	Bloomberg
	Central Bank Transparency	Dincer and Eichengreen (2014)
	Core Inflation	Haver Analytics
	Credit Default Swap Spreads	Refinitiv Datastream, IMF staff calculations
	Current Account	Haver Analytics
	Fiscal balance	Haver Analytics
	Inflation Expectations (1-,2-,3-,5-,10-years ahead)	Consensus Economics; Bureau for Economic Research
	Nominal Effective Exchange Rate	Bloomberg Finance L.P., IMF staff calculations
	Oil futures price	Bloomberg Finance L.P., IMF staff calculations
Sectoral Price Dispersion and Inflation	Commodity Prices (Food and Energy)	IMF, International Financial Statistics
	Consumer Price Index	IMF CPI database
	External Price Pressure	IMF staff calculations
	Industrial Production	Haver Analytics
	Inflation expectations	Consensus Economics
	Unemployment Rate	Haver Analytics
Semiconductors Price	Input-Output Tables	U.S. Bureau of Economic Analysis
	Import Prices of Semiconductors	U.S. Bureau of Labor Statistics
	Personal Consumption Expenditure	U.S. Department of Commerce, U.S. Bureau of Economic Analysis

Annex Table 2.1.2 Sample of Economies included in Analytical Exercises

Figure	Countries
Inflation and Labor Demand (Figure 2.3)	Australia, Austria, Belgium, Canada, Czech Repubilc, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Japan, Netherlands, Norway, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States
Unemployment Gap—Inflation Phillips Correlation (Figure 2.4)	Australia, Austria, Belgium, Brazil*, Bulgaria*, Canada, Chile*, China*, Colombia*, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong SAR, Hungary*, India*, Indonesia*, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Malaysia*, Mexico*, Netherlands, New Zealand, Norway, Peru*, Philippines*, Poland*, Portugal, Romania*, Russia*, Singapore, Slovak Republic, Slovenia, South Africa*, Spain, Sweden, Switzerland, Thailand*, Turkey*, United Kingdom, United States
Slack Induced Inflation Dynamics from Structural Phillips Curve in Advanced Economies (Figure 2.5)	Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong SAR, Ireland, Italy, Japan, Korea, Latvia, Lithuania, Netherlands, New Zealand, Norway, Portugal, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States
Inflation Anchoring (Figure 2.6, panel 1)	Argentina*, Australia, Brazil*, Bulgaria*, Canada, Chile*, China*, Colombia*, Croatia*, Czech Republic, Estonia, France, Germany, Hong Kong SAR, Hungary, India*, Indonesia*, Italy, Japan, Korea, Latvia, Lithuania, Malaysia*, Mexico*, Netherlands, New Zealand, Norway, Peru*, Philippines*, Poland*, Romania*, Russia*, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Thailand*, Turkey*, Ukraine*, United Kingdom, United States, Venezuela*
Inflation Anchoring (Figure 2.6, panel 2)	Argentina*, Australia, Brazil*, Bulgaria*, Canada, Chile*, China*, Colombia*, Croatia*, Czech Republic, Estonia, France, Germany, Hungary, India*, Indonesia*, Italy, Japan, Korea, Latvia, Lithuania, Malaysia*, Mexico*, Netherlands, New Zealand, Norway, Peru*, Philippines*, Poland*, Romania*, Russia*, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Taiwan Province of China*, Thailand*, Turkey*, Ukraine*, United Kingdom, United States, Venezuela*
Inflation Anchoring (Figure 2.6, Panel 3)	Argentina*, Australia, Brazil*, Chile*, China*, Colombia*, Estonia, France, Germany, Hong Kong SAR, Hungary, Indonesia*, Italy, Japan, Korea, Latvia, Lithuania, Malaysia*, Mexico*, Netherlands, New Zealand, Norway, Peru*, Philippines*, Poland*, Romania*, Russia*, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Thailand*, Turkey*, Ukraine*, United Kingdom, United States, Venezuela*
Inflation Episodes (Figure 2.7)	Argentina*, Australia, Brazil*, Bulgaria*, Canada, Chile*, China*, Colombia*, Croatia*, Czech Republic, Estonia, France, Germany, Hong Kong SAR, Hungary, India*, Indonesia*, Italy, Japan, Korea, Latvia, Lithuania, Malaysia*, Mexico*, Netherlands, New Zealand, Norway, Peru*, Philippines*, Poland*, Russia*, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Taiwan Province of China*, Thailand*, Turkey*, Ukraine*, United Kingdom, United States
Responses of Five-Year, Five-Year Forward Breakeven Inflation to Oil Price Shocks (Figure 2.8)	Australia, Brazil*, Canada, Chile*, France, Germany, Israel, Italy, Japan, Mexico*, South Africa*, Sweden, United Kingdom, United States
Headline Inflation and Inflation Expectations Outlooks—Three Scenarios (Figure 2.10, Figure 2.11, and Figure 2.12)	Advanced Economies: Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hong Kong SAR, Ireland, Italy, Japan, Korea, Latvia, Lithuania, Netherlands, Norway, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States Emerging Market Economies: Bangladesh*, Bulgaria*, Chile*, China*, Colombia*, Costa Rica*, Ecuador*, Egypt*, El Salvador*, Honduras*, Hungary*, Malaysia*, Mexico*, Moldova*, Pakistan*, Paraguay*, Philippines*, Poland*, Russia*, South Africa*, Thailand*, Turkey*, Ukraine*, Uruguay*, Vietnam*

Source: IMF staff compilation.

Note: Asterisk(*) denotes emerging market and developing economies as classified by the April 2021, World Economic Outlook.

Annex 2.2 Phillips Curve Estimation

This section describes the reduced form and causal estimations of the relationship between economic slack and inflation. The chapter's starting point for the empirical investigation is a reduced form hybrid variant of a standard New Keynesian Phillips curve. Drawing on IMF (2018), we augment the baseline hybrid Phillips Curve (Gali and Gertler, 1999; Gali, Gertler, and Lopez-Salido, 2001, 2003) with open economy variables that proxy for macroeconomic developments in the rest of the world (Borio and Filardo, 2007; Ihrig and others 2010; Auer, Borio, and Filardo 2017; Bems, Caselli, Grigoli, and Gruss 2020). Specifically, the chapter starts with an estimate of the following model:

$$\pi_{i,t} = \beta_1\pi^e_{i,t} + \beta_2\pi_{i,t-1} + \beta_3 y^{dom}_{i,t} + \beta_4 y^{for}_{i,t} + \beta_5 \Delta P^*_{i,t} + FE + \varepsilon_{i,t} \qquad (2.2.1)$$

where *i* indexes the country, *t* the quarterly time period. Annualized quarter-over-quarter core CPI inflation $\pi_{i,t}$ is regressed on the following covariates. $\pi^e_{i,t}$ is the three-year ahead inflation expectation from Consensus Economics, $\pi_{i,t-1}$ is lagged inflation, $y^{dom}_{i,t}$ is, depending on the specification, the domestic output or unemployment gap, $y^{for}_{i,t}$ is the foreign output gap, FE captures both country and time fixed effects, $\Delta P^*_{i,t}$ captures external price pressures (Eq. 2.2.2). It is defined as the percent change in the import-weighted producer price index (PPI) of countries from which country *i* imports, converted to local currency using the nominal effective exchange rate, and relative to the percent change in the GDP deflator

$$\Delta P^*_{i,t} = \Delta mPPI_{i,t} + \Delta neer_{i,t} - \Delta P_{i,t} \qquad (2.2.2)$$

in which $P_{i,t}$ is the natural logarithm of country i's GDP deflator. The change in the import-weighted foreign PPI is given by

$$\Delta mPPI_{i,t} = \sum_{j=1}^{J} \omega_{ij,t} \Delta PPI_{j,t} \ , \qquad i \neq j \ ,$$

in which $PPI_{j,t}$ is the natural logarithm of country i's producer price index; and $\omega_{ij,t}$ is the share of exports from country j in country i's total annual imports.

The change in the nominal effective exchange rate is constructed as the change in the bilateral exchange rate of each trading partner vis-à-vis the US dollar, weighted by their import shares (Gopinath 2015; Carrière-Swallow and others 2016).

$$\Delta neer_{i,t} = \sum_{j=1}^{J} \omega_{ij,t}(\Delta e_{i,t} - \Delta e_{j,t}) \ , \qquad i \neq j \ ,$$

in which, $e_{i,t}$ is the natural logarithm of country *i*'s bilateral exchange rate (expressed in local currency per US dollar, so that an increase denotes a depreciation of the domestic currency); and Δ is the first difference operator.

The foreign output gap is defined as:

$$Y_{i,t}^{*Gap} = \sum_{j=1}^{J} \omega_{ij,t} Y_{j,t}^{Gap} \ , \qquad i \neq j \ ,$$

in which $Y_{j,t}^{Gap}$ is the Hodrick-Prescott filtered series of real GDP of country *j*.

The domestic output gap is the difference between the actual and potential output in percent of potential output, where potential is estimated as a HP-filtered underlying trend of output. Similarly, the unemployment gap is the percentage point difference between HP-filtered unemployment and actual unemployment.

Annex Table 2.2.1 presents the results for the output gap and the unemployment gap for all economies, advanced economies, and emerging economies. The coefficients on the output gap and unemployment gap are the ones visualized in the Figure 2.4 in the main text. The remaining coefficients are intuitive. Inflation expectations matter, more so in Advanced Economies (AEs), which presumably had more success with inflation targeting, than in Emerging Economies (EMs). Conversely, the backward-looking component is more important, indicating inflation of a more adaptive nature, in EMs compared to AEs. The impact of external price pressures is also more pronounced for EMs that are likely to display more small open economy features in their business cycles dynamics.

Annex Table 2.2.1 Hybrid Phillips Curve: Baseline Estimation Results

VARIABLES	(1) Core Unemployment gap All 2000-19 (OLS) cluster	(2) Core Output gap All 2000-19 (OLS) cluster	(3) Core Unemployment gap AEs 2000-19 (OLS) cluster	(4) Core Output gap AEs 2000-19 (OLS) cluster	(5) Core Unemployment gap EMs 2000-19 (OLS) cluster	(6) Core Output gap EMs 2000-19 (OLS) cluster
Inflation expectations 3 years ahead	0.681***	0.688***	0.935***	0.913***	0.307***	0.353***
	(0.207)	(0.195)	(0.215)	(0.207)	(0.085)	(0.109)
Lag of core price inflation	0.311**	0.297**	0.096	0.096	0.551***	0.511***
	(0.124)	(0.118)	(0.073)	(0.074)	(0.038)	(0.061)
Unemployment gap	-0.304**		-0.201*		-0.483**	
	(0.121)		(0.099)		(0.193)	
Lag of external price pressure	0.026***	0.026***	0.009**	0.009**	0.032***	0.032***
	(0.007)	(0.007)	(0.004)	(0.004)	(0.009)	(0.010)
Foreign output gap	0.296*	0.251	0.553***	0.537***	0.225	0.216
	(0.148)	(0.151)	(0.174)	(0.187)	(0.231)	(0.235)
Output gap		0.154***		0.117***		0.215**
		(0.042)		(0.042)		(0.079)
Observations	2,054	2,061	1,279	1,285	775	776
R-squared	0.713	0.705	0.391	0.395	0.795	0.768
Adjusted R-squared	0.697	0.689	0.348	0.351	0.774	0.745
Within R-square	0.445	0.424	0.179	0.182	0.604	0.562

Sources: Consensus Economics; Haver Analytics; IMF, Direction of Trade Statistics; and IMF staff calculations.
Note: Robust standard erros are in parentheses. AEs = advanced economies; EMs = emerging market economies; OLS = Ordinary Least Squares.
* $p<0.1$; ** $p<0.05$; *** $p<0.01$

Annex Table 2.2.2 presents results using median inflation as a dependent variable in columns (1) and (2) for a set of emerging economies (Brazil, Chile, India, Malaysia, Mexico, Philippines, Poland, Romania, Russia, South Africa, Thailand, Turkey) where such a measure could be constructed. The estimated coefficients are broadly in line with the baseline results. Estimation results in columns (3) to (8) present results that add a squared term in the output and unemployment gap to equation 2.2.1 to check for nonlinear effects at high levels of slack (for a discussion see for instance Kumar and Orrenius 2016, among others). The results present mixed evidence of nonlinear effects in this sample.

Annex Table 2.2.2 Hybrid Phillips Curve: Median Inflation Measures and Nonlinearities

VARIABLES	(1) Median (NSA) Unemployment gap EM 2000Q1–19Q4 (OLS)	(2) Median (NSA) Output gap EM 2000Q1–19Q4 (OLS)	(3) Core Unemployment gap All 2000Q1–19Q4 (OLS)	(4) Core Output gap All 2000Q1–19Q4 (OLS)	(5) Core Unemployment gap AE 2000Q1–19Q4 (OLS)	(6) Core Output gap AE 2000Q1–19Q4 (OLS)	(7) Core Unemployment gap EM 2000Q1–19Q4 (OLS)	(8) Core Output gap EM 2000Q1–19Q4 (OLS)
Inflation expectations 3 years ahead	1.173***	1.180***	0.681***	0.685***	0.914***	0.907***	0.311***	0.348***
	(0.071)	(0.084)	(0.207)	(0.192)	(0.223)	(0.213)	(0.086)	(0.097)
Lag of core price inflation	0.147	0.166	0.310**	0.296**	0.094	0.095	0.551***	0.504***
	(0.097)	(0.097)	(0.124)	(0.118)	(0.072)	(0.073)	(0.037)	(0.061)
Unemployment gap	-0.641***		-0.309**		-0.231**		-0.503***	
	(0.200)		(0.123)		(0.107)		(0.172)	
Lag of external price pressure	0.035**	0.034**	0.026***	0.026***	0.009**	0.009**	0.032***	0.031***
	(0.014)	(0.015)	(0.007)	(0.007)	(0.004)	(0.004)	(0.009)	(0.009)
Foreign output gap	-0.329	-0.176	0.297**	0.247	0.553***	0.535***	0.253	0.193
	(0.625)	(0.502)	(0.148)	(0.150)	(0.173)	(0.185)	(0.209)	(0.222)
Squared unemployment gap			0.009		0.030		-0.081	
			(0.023)		(0.022)		(0.055)	
Output gap		0.236***		0.151***		0.117***		0.199**
		(0.067)		(0.042)		(0.042)		(0.081)
Squared output gap				0.008		0.002		0.027***
				(0.006)		(0.005)		(0.006)
Observations	418	428	2,054	2,061	1,279	1,285	775	776
R-squared	0.670	0.666	0.713	0.705	0.393	0.395	0.796	0.770
Adjusted R-squared	0.607	0.604	0.697	0.690	0.349	0.351	0.774	0.746

Sources: Consensus Economics; Haver Analytics; IMF, Direction of Trade Statistics; and IMF staff calculations.
Note: Robust standard erros are in parentheses. AE = advanced economies; EM = emerging market economies; NSA = not seasonally adjusted; OLS = Ordinary Least Squares.
* p<0.1; ** p<0.05; *** p<0.01

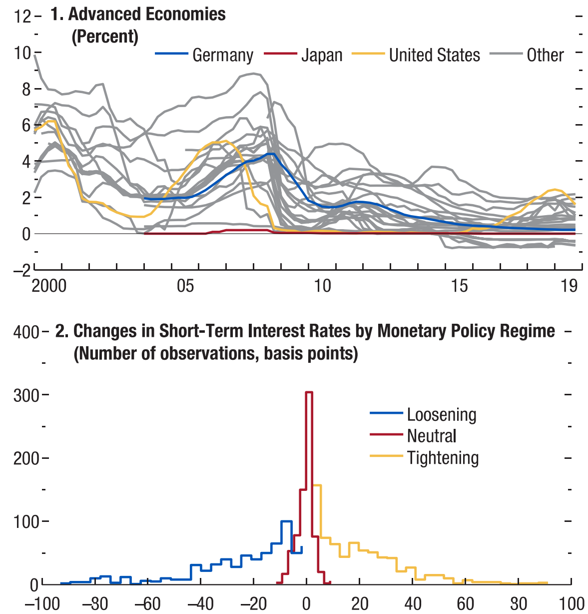
A causal Phillips curve estimation

To address endogeneity concerns due to omitted variables bias and simultaneity (see main text for a discussion), the chapter presents results where the unemployment rate is instrumented via monetary policy shocks. The results are presented for a sample of 31 advanced economies for the period from 2000 Q1 to 2019 Q4. The dependent variable is year-on-year changes in core inflation. The endogenous explanatory variable of interest is the unemployment rate. Regressions also include 3-year ahead inflation expectations from Consensus Forecasts, an index for imported foreign price pressures from Eq. (2.2.2), as well as changes in nominal short-term interest rates. All variables, including the dependent variable, enter the estimating equation with up to 3 quarterly lags.

To identify monetary policy shocks, the chapter relies on a treatment effects framework. This entails discretizing changes in nominal short-term interest rates and assigning them to one of three 'treatment' groups based on the direction and size of the change. Specifically, for every country we assign quarter-on-quarter changes in nominal short-term interest rates in equal proportion to either a Loosening, Neutral or Tightening stance based on the country's history. For example, the highest third of quarterly increases in short-term nominal interest rates based on the country's history will be assigned a Tightening stance. This approach reduces information on monetary policy changes that would be available in a standard linear model since monetary policy now only takes one of three distinct values based on the 'treatment' received, i.e. a Loosening, Neutral or Tightening stance. However, the advantage of the approach is that it allows for a more credible and transparent identification of monetary policy shocks. Annex Figure 2.2.1 presents the distribution of quarter-on-quarter short-term interest rate changes in the sample. Despite the zero-lower bound, short-term interest rates do vary in this sample of AEs providing variation for the instrumentation procedure.

Annex Figure 2.2.1. Short-Term Interest Rates

Despite the zero-lower bound, changes in short-term interest rates are frequent in the sample considered for the structural Phillips curve estimation.



Sources: Haver Analytics; and IMF staff calculations.

To give some intuition for the approach, consider the case of a central bank that keeps its policy rate unchanged while inflation declines from weak demand. The treatment effects method used in the chapter would treat this as a 'surprise' outcome since it would diverge from an expected Taylor rule-type behavior. This observation in the sample would therefore be a good control that could be matched to similar periods of weak demand and inflation where the central bank did in fact lower its policy rate. The treatment effects approach provides a systematic and data-driven way of identifying these unexpected monetary policy actions. The chapter follows the semi-parametric identification approach outlined in Angrist, Jordà and Kuersteiner (2018) where the probability of a change in the monetary policy stance is modeled using an ordered logit with lags of the dependent and explanatory variables used as predictors $(z_{i,t})$. Inverse probability weighting (IPW) using the parametrically estimated propensity scores allows one to non-parametrically estimate counterfactual outcomes for inflation and unemployment had a monetary policy tightening *not* taken place in the quarter.

The impact of a surprise monetary policy tightening can be estimated by comparing the average outcomes across the group of observations depending on the monetary policy stance. Specifically, at horizon h, the causal impact can be estimated by taking the difference between the average predicted outcome $(\hat{\pi}_{i,t+h})$ for observations where the stance was unexpectedly tightened $(D_{i,t} = T)$ to the average of the reweighted observations (with inverse propensity weights $\frac{\hat{p}_T(z_t)}{\hat{p}_N(z_t)}$) where the stance was neutral $(D_{i,t} = N)$

$$\hat{\gamma}^h = \frac{1}{N}\sum_n \left[\hat{\pi}_{i,t+h}\left(1\{D_{i,t} = T\} - \frac{\hat{p}_T(z_t)}{\hat{p}_N(z_t)}1\{D_{i,t} = N\}\right)\right]. \quad (2.2.3)$$

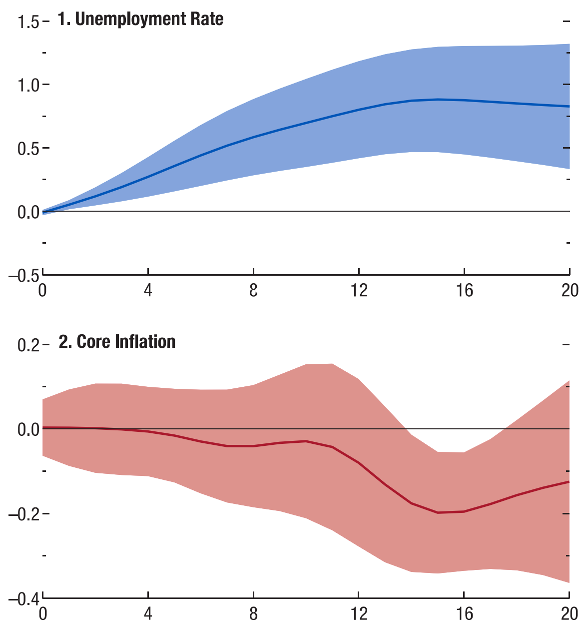
In addition to the IPW adjustment in Eq. (2.2.3), we rely on regression adjustment (RA), which entails replacing the outcome variable $\pi_{i,t+h}$ with its predicted value based on a group-specific linear model using the same instruments $z_{i,t}$ as for the ordered logit estimate

$$\hat{\pi}_{i,t+h} = \hat{\beta}^{RA} z_{i,t}.$$

Combining IPW and RA provides double-robustness to our identifying assumption (Imbens and Wooldridge 2009). Estimates of $\hat{\gamma}^h$ at various horizons show the impulse response functions of the unemployment rate and core inflation to an average cumulative tightening of monetary policy of 40 basis points.[1] Figure 2.2.2, panel 1 shows the unemployment rate increases by 1 percentage point on average in response to a cumulative 40 basis points surprise tightening, compared to a neutral stance, and the full impact takes about 12 quarters to materialize. Figure 2.2.2, panel 2 shows that core inflation significantly decreases by around 0.2 percentage point after 15 quarters to the same sequence of monetary policy tightening.[2]

Annex Figure 2.2.2. Response of Unemployment and Core Inflation to Monetary Policy Tightening
(Percentage points)

A monetary policy tightening gradually raises the unemployment rate and lowers inflation.



Source: IMF staff calculations.
Note: The solid lines represent the smooth local projection; the shaded areas represent 90 percent confidence intervals. The *x*-axis indicates the number of quarters after the monetary tightening starts.

While the estimated impulse response function for the unemployment rate is on the higher end, it is consistent with the empirical literature that exploits narrative approaches to estimate the effects of monetary policy shocks on real activity (Ramey 2016, Table 2). Moreover, it is important to stress the differences in terms of sample period and composition and estimation approach compared with the bulk of the literature that focuses on linear models in the US. Notably, the sample used in the chapter includes several Euro area countries where, even through the lens of structural DSGE models with labor markets, monetary policy explains twice or thrice the variation in unemployment (Mihailov, Razzu, and Wang 2019, Table 5) compared to the standard US results (in Galì, Smets, Wouters 2012). In addition, the impulse responses of

[1] Impulse response functions are estimated using smooth local projections (Barnichon and Brownlees 2019). The average cumulative tightening of 40 basis points is the peak difference between nominal short-term interest rates in the Tightening and Neutral regimes following a surprise tightening. This peak is reached after 4 quarters.

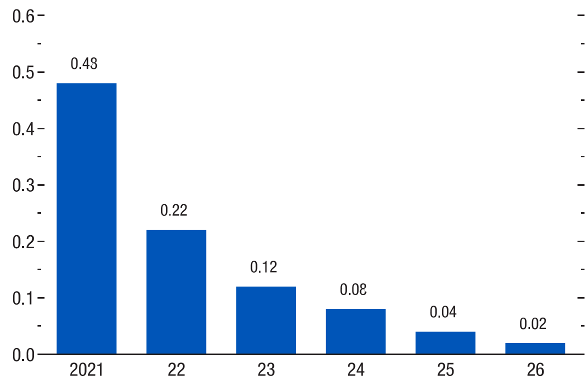
[2] The timing of the effect of monetary policy contractions on unemployment and core inflation is consistent with Barnichon and Mesters (2020). Ramey (2016) reports the trough effects of 100 basis point funds peak as varying between 4 and 6 quarters.

unemployment and inflation to a monetary loosening are smaller than those following a tightening, i.e. the “pushing on a string” metaphor (Angrist and others 2016). The treatment effects approach allows the estimation of these asymmetric effects, unlike standard linear VARs which implicitly assume the same marginal effects of loosening and tightening. This biases the VAR impulse responses of a tightening towards zero, a feature we also find when averaging the impulse responses of loosening and tightening using our approach.

As discussed in Barnichon and Mesters (2021), the ratio of the two impulse response functions yields an instrumental variable estimate of the Phillips curve coefficient. These estimates suggest a Phillips curve coefficient estimate of -0.22 (standard error of 0.09; p-value 0.02) which is derived by taking the ratio of the impulse response functions from lags 14 to 16 when the instrument has sufficient explanatory power (e.g. when the first stage passes standard significance tests).

Annex Figure 2.2.3. Slack-Induced Inflation Dynamics from Reduced Form Phillips Curve in Emerging Market Economies
(Percentage points)

Short-term inflation dynamics from slack as measured by the output gap are moderate for emerging market economies.



Sources: Haver Analytics; and IMF staff calculations.
Note: The bars represent the inflationary impulse from changes in the output gap based on the October 2021 *World Economic Outlook* vintage and the structural Phillips curve estimation described in the chapter.

For AEs, this estimate is combined with the forecasted changes in the unemployment gaps from the most recent vintage of the World Economic Outlook to summarize the expected contribution of slack to inflation in advanced economies (Figure 2.5 in the main text). Generating credible instruments for EMs is more challenging than for AEs and long-run unemployment gap projections are also not available for EMs.

Annex Figure 2.2.3 uses the reduced form coefficient on the output gap version of the Phillips Curve from Annex Table 2.2.1 (column 6) to determine the projected contribution of recovering demand to inflation. The slack-induced inflation dynamics in EMs are somewhat more pronounced than in the AEs adding about one half-percentage point in the year 2021.

Annex 2.3. Inflation Expectations Anchoring

Inflation acceleration episodes

To focus on how inflation expectations and policy responses evolve around turning points in inflation, the analysis identifies inflation accelerations using an approach similar to that of Hausmann, Pritchett, and Rodrik (2005) for growth performance. The sample consists of 43 countries on which both quarterly inflation data and professional forecasters’ (consensus forecasts) data is available, from 1998 Q1 onwards. AEs comprise 60 percent of the sample, and EMs the other 40 percent. The inflation rate is measured as the year-on-year change in the quarterly CPI.

Instances of rapid acceleration in inflation that are sustained for at least 2 quarters are identified as follows (and episodes that last at least 3, 4, 5, and 6 quarters are classified similarly):

(1) The episode starts with an acceleration: the *change in* the inflation rate is at least 0.75.

(2) The inflation rate is at least 3.5 percent in each period in AEs, and at least 10 percent in each period in EMs.[3]

(3) The episodes are at least 3 years apart. (Any episode that had one within three years before it is dropped.)

The procedure yields 55 episodes that last at least 2 quarters. Annex Table 2.3.1 shows the distribution of episodes across country group and length.

Annex Table 2.3.1 Inflation Episodes

Episode length:	At least 2 quarters	At least 3 quarters	At least 4 quarters	At least 5 quarters	At least 6 quarters
Panel A. Number of Episodes					
Advanced economies	28	20	18	9	7
Emerging markets	27	23	21	16	10
Total	55	43	39	25	17
Panel B. Frequency of Episodes *(Percent)*					
Advanced economies	1.3	0.9	0.8	0.4	0.3
Emerging markets	2.3	1.9	1.7	1.2	0.7
Total	1.6	1.2	1.1	0.7	0.4

Source: IMF staff calculations.
Note: Table shows the number and frequency of inflation acceleration episodes in the 43 country sample since 1995. Frequency is the number of inflation episodes divided by number of data points in that region.

As discussed in the main chapter, inflation acceleration episodes coincide with large currency deprecations in EMs. Before the start of an episode, the main noticeable difference is that larger exchange rate depreciations occur in the episodes that end up being longer.

Annex Table 2.3.2 Inflation Episodes Summary Statistics

Panel A. Before Episodes	Previous Mean	Just Prior Mean	Difference Mean	Difference *p-values*
NEER (% change qoq)	-1.1	-2.4	-1.3	0.05
Current account (percent GDP)	-0.3	-0.7	-0.4	0.61
Fiscal balance	-1.1	-1.2	-0.2	0.78
Expectations 3-years ahead	5.1	5.3	0.1	0.79

Note: Table reports difference in average value of variable just prior to the start of an acceleration (from t-3 to t-1) compared to the previous 6 quarters (t-9 to t-4).

Analysis of market-based inflation expectations

This section analyses the drivers of market-based measures of inflation expectations. Central banks follow these measures closely as they (i) incorporate new information rapidly and (ii) reflect the views of investors with money at stake. The main measure analyzed is the five-year-five-year forward breakeven inflation rate. For a given maturity bond, the breakeven inflation rate is calculated as the difference between the yield on conventional bonds and comparable inflation-indexed bonds. This is the level of expected inflation at which an investor would be indifferent between holding either bond. The 5-year (spot) breakeven rate, for example, is a

[3] In the country sample after 2004: the 90th percentile of changes in the inflation rate is 0.75 for AEs, and 1.5 for EMs; the 90th percentile of inflation rate is 3.35 percent in AEs and 10 percent in EMs.

measure of the average expected inflation rate over the next 5 years. The five-year-five-year forward breakeven rate is calculated as follows using spot-forward parity condition to calculate the five and ten-year forward rates:

$$\pi_{i,t}^{e,LT} = BE5Y5Yforward_{it} = \left(\frac{(1+BE10_{it})^{10}}{(1+BE5_{it})^{5}}\right)^{1/(10-5)} - 1 \qquad (2.3.1)$$

The data on bond yields is daily, from Bloomberg, and the sample consists of 14 countries ,11 AEs and 3 EMs, that issue inflation-indexed bonds at both 5- and 10-year maturities.

Building on the literature (Gürkaynak, Sack, and Wright 2010; Beechey, Johannsen, and Levin 2011, Celasun, Mihet, and Ratnovski 2012) the analysis uses local projections (Jordà 2005) to trace the response of the five-year-five-year forward breakeven rate to oil price shocks. The analysis employs oil price surprises as a proxy for inflation surprises as in IMF (2016). Oil price surprises are measured as the daily percentage change in prices on one-year ahead futures contracts. The controls are: ten lags of the dependent variable $\Delta\pi_{i,t-p}^{e,LT}$, the daily percentage change in the nominal effective exchange rate $NEER_{i,t}$ and its ten lags, the daily change in the VIX $VIX_{i,t}$ and its ten lags, and month and country fixed effects, τ_{month}^{h} and α_i^h respectively.

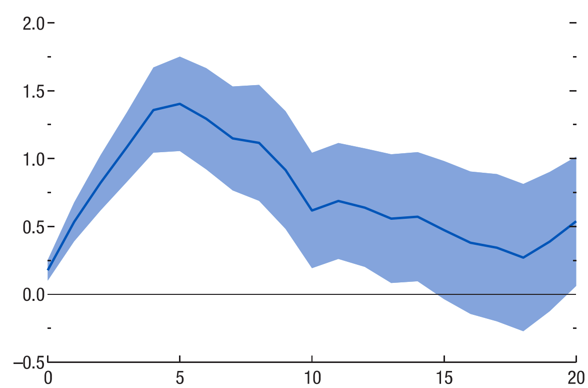
$$\Delta\pi_{i,t+h}^{e,LT} = \alpha_i^h + \tau_{month}^h + \sum_{p=0}^{P}\Delta\pi_{i,t-p}^{e,LT} + \sum_{p=0}^{P}\beta_p^h Oil_{t-p} + \sum_{p=0}^{P}\delta_p^h NEER_{i,t-p} + \sum_{p=1}^{P}\rho_p^h VIX_{i,t-p} + \varepsilon_{i,t+h} \qquad (2.3.2)$$

The baseline result (Figure 2.8 in main text) is that a one percentage point increase in the oil futures price is associated with a one basis point change in the expectations measure five days after the shock, with the effect lasting about two weeks. The analysis also explores whether there are non-linearities in the relationship between oil price shocks and inflation expectations. No evidence of non-linearities is found, as the response to large oil price shocks is not statistically significantly different from the average response.

A robustness exercise is conducted, where the breakeven rate is cleaned of liquidity risk premia following Gürkaynak and others (2010). In addition to reflecting inflation compensation, breakeven rates include liquidity risk and inflation risk premia. The inflation-risk premia, which reflects investors' uncertainty about future inflation and increases breakeven rates, is not extracted. This is similar to Beechey and others (2011) and Strohsal and Winkelmann (2015), since this uncertainty is a relevant component of anchoring that central banks seek to minimize.[4] The five-year-five-year forward

Annex Figure 2.3.1. Response of Liquidity Adjusted Five-Year, Five-Year Forward Breakeven Inflation to Oil Price Shocks
(Basis points)

The response of the market-based inflation expectations measure cleaned of liquidity premia is similar to that of the simple (unadjusted) five-year, five-year forward breakeven rate.



Sources: Bloomberg Finance L.P.; and IMF staff calculations.
Note: The solid line represents the estimated response; the shaded areas represent 95 percent confidence intervals. The *x*-axis indicates the number of days after the shock starts.

[4] For the US, Goel and Malik (2021) find that recent increase in the five-year five-year forward breakeven is due mostly to an increase in the inflation risk premium, whereas for the shorter horizon 5-year breakeven the increase is about half from an increase in expected inflation and half from an increase in inflation risk premia.

breakeven rate is adjusted for the relative liquidity premia of the nominal and inflation-indexed bond markets as follows: (1) For each country, the time-varying effect of liquidity on inflation compensation is measured as the negative of the fitted values from a regression of the five-year-five-year forward breakeven rate on liquidity proxies for both the nominal and inflation-indexed bonds. The liquidity proxies used are the daily bid-ask spreads, which are available for a subset of 10 countries in the sample. Trading volumes, which are another indicator of liquidity and used in the literature on the US, are not available for a sufficiently long time period for other countries to employ in the estimation. This method captures the time variation but not the level of the liquidity premium. Thus, the level of the liquidity premium is normalized to have a minimum of zero, by country. (2) The normalized liquidity premium is then added to the five-year-five-year forward breakeven rate, to obtain the rate cleaned of liquidity risk premia.

$$BE5Y5Yfoward_{it} = \pi_{it}^{adjusted} - LiquidityRisk_{it} \qquad (2.3.3)$$

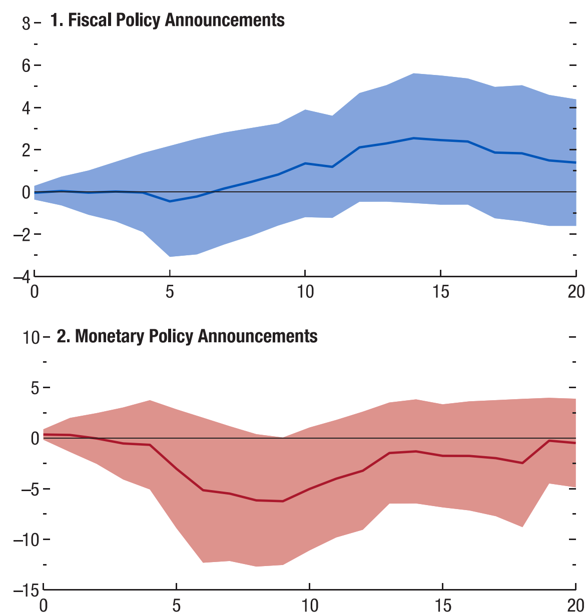
The response of the adjusted market-expectations measure to oil price shocks is very similar to that of the measure that is not cleaned of liquidity premia (Annex Figure 2.3.1).

Effects of policy announcements

Finally, this section analyzes the announcement effects on market-based inflation expectations of the expansionary fiscal and monetary policy measures taken in response to the pandemic. The data on announcements of COVID-19 response policies is from the Yale Program on Financial Stability (YPFS) COVID-19 Financial Response Tracker and covers the period from February 2020 to June 2021. The empirical specification is the same as in equation (2.3.1) except for the inclusion of dummy variables for each of the fiscal and monetary policy announcements, that are equal to 1 on the day of an expansionary announcement and 0 otherwise. In the sample, there are 79 days with announcements of fiscal measures, and 69 days where monetary policy actions. Market-based long-term expectations have not responded, on average, to the policy announcements (Annex Figure 2.3.2). Since the 14 countries in the sample have high central bank credibility and well-anchored inflation expectations, the effects of policy announcements in countries with less well-anchored expectations could be larger. Moreover, the fiscal policymaking process can be lengthy with information about expected measures possibly being priced-in before the actual announcement.

Annex Figure 2.3.2. Response of Five-Year, Five-Year Forward Breakeven Inflation to Policy Announcements
(Basis points)

Fiscal and monetary policy announcements during the pandemic have not caused market-based expectations to increase, on average.



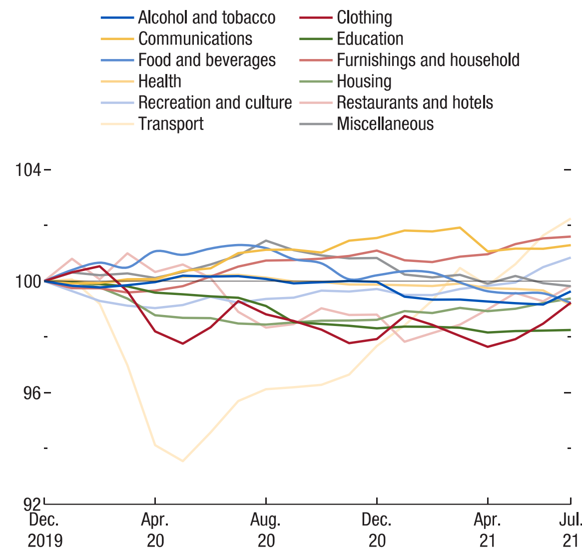
Sources: Bloomberg Finance L.P.; IMF, COVID-19 Policy Tracker; and IMF staff calculations.
Note: The solid lines represent the estimated response; the shaded areas represent 95 percent confidence intervals. The *x*-axis indicates the number of days after the policy announcement.

Annex 2.4. Sectoral Price Dispersion and Inflation

The chapter uses data from the IMF's CPI database, which includes consumer price data for around 150 countries representing 85 percent of global GDP in 2019 in PPP terms. The database includes the headline CPI index as well as 12 harmonized consumption categories (an example of the disaggregation is displayed in Annex Figure 2.4.1). The chapter's measure of sectoral inflation dispersion is the weighted standard deviation of the year-on-year inflation for the 12 consumption components in a given country and month, where the weights are the share of total consumption, also reported in the CPI database.[5] In addition to sectoral inflation dispersion, the chapter uses headline year-on-year monthly inflation from the CPI database. The sample extends from January 2000 to June 2021.

Annex Figure 2.4.1. Sectoral Consumer Price Levels
(Index, December 2019 = 100)

The COVID-19 crisis led to large price movements in some sectors, notably transportation, food, clothing, and communications



Sources: IMF, CPI database; and IMF staff calculations.
Note: The lines are averages weighted by country's purchasing-power-parity GDP.

Supply disruptions: the case of semiconductors

A combination of increased demand for certain products, such as electronics, and stringent lockdown measures to contain the spread of the virus prompted supply chain disruptions and supply shortages in several sectors during the pandemic crisis. One area which has received considerable attention is the semiconductor sector, which has experienced severe shortages since the beginning of the pandemic. What could be the impact of a sharp increase in semiconductors' prices going forward? The first piece of evidence is that the import price of semiconductors did not increase substantially in recent months in the United States, hence indicating moderate risks coming from higher prices of chips produced abroad and imported domestically (Annex Figure 2.4.2, panel 1). Since semiconductors do not enter the consumption basket directly, but are rather used as inputs to produce final goods, a back of the envelope calculation exploiting input-output tables is performed to assess the effects of a potential doubling of semiconductors input prices on goods and services consumed in the United States. Annex Figure 2.4.2, panel 2, shows that categories with the highest increase in inflation as a result of the doubling input price of semiconductors have a very small weight in the personal consumption expenditure (PCE) basket (i.e. personal computers and photographic equipment). On the contrary, consumptions items that exhibit a negligible increase in prices due to the increased semiconductors prices (e.g. housing) have the highest weights in the consumption basket. On average, the overall impact on

[5] China's National Bureau of Statistics does not report consumption shares for inflation component series. We estimate constant shares using a constrained regression of headline inflation on component inflation, where estimated weights are between zero and one and sum to one. Component price data for the US are taken from the Bureau of Labor Statistics and from Statistics Canada for Canada. For Japan and Eurostat-reporting countries, we use the indirect tax-adjusted headline inflation series. Headline inflation rates in 2021 for euro area countries are also adjusted for changes in the consumption baskets.

PCE inflation would be a 0.3 percent increase suggesting that even an extreme scenario of semiconductors input price increases would have a moderate effect on US consumer price inflation.[6]

VAR based forecasts of inflation risks

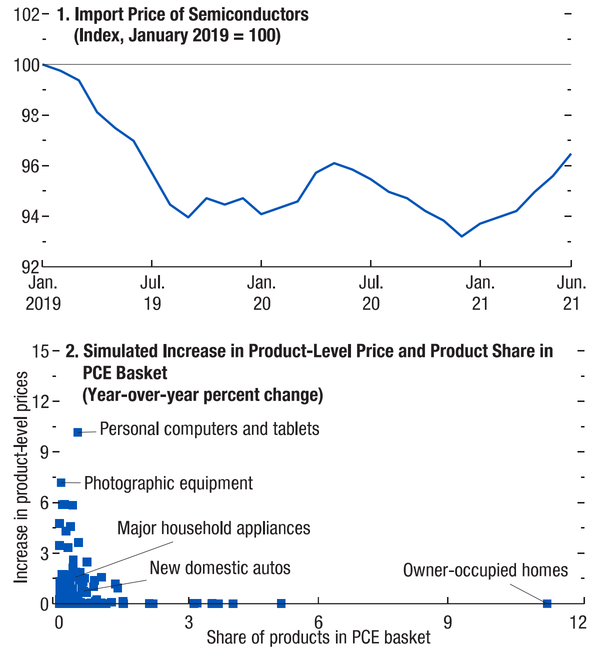
To construct dynamic forecasts for inflation, the chapter estimates the following structural VAR for each advanced economy in the sample.[7]

$$\mathbb{Q}^{\tau}(Y_{t+1}|Y_t) = \mu^{\tau} + \delta_1^{\tau} Y_{t+1} + \sum_{s=0}^{S} \delta_{-s}^{\tau} Y_{t-s}, \quad (2.4.1)$$

where Y_t is a vector consisting of 7 endogenous variables including (in order): global commodity prices for energy and food, an external price pressure index that calculates the difference between domestic and import-weighted inflation of trading partners minus changes in the nominal exchange rate (Gopinath 2015; Carrière-Swallow and others 2016), the unemployment rate for advanced economies and year-on-year changes in industrial production for emerging market and developing economies, sectoral inflation dispersion, 3-year ahead inflation expectations from Consensus Forecasts, and finally headline inflation. The above Cholesky ordering means that global energy prices are not allowed to respond to contemporaneous shocks to other variables in the system, food prices only respond to contemporaneous shocks in energy prices, and so on. Headline inflation, on the other hand is allowed to respond to contemporaneous shocks to all other variables.[8] These identifying assumptions are implicit in the strictly lower triangular matrix δ_1^{τ}. Finally, Eq. (2.4.1) extends the traditional linear VAR by estimating a system of quantile regressions instead (Koenker and Xiao 2006; Montes-Rojas 2019; Ghysels, Iania and Striaukas 2018; Boire, Duprey and Ueberfeldt 2021; Chavleishvili and Manganelli 2020).[9]

Annex Figure 2.4.2. Semiconductor Price Effect on Inflation in the United States

The price of semiconductor imports in the United States did not increase substantially since the beginning of the pandemic. Even a potential doubling of the price of semiconductors input will only have minor effect on overall inflation.



Sources: US Bureau of Economic Analysis; US Bureau of Labor Statistics; and IMF staff calculations.
Note: In panel 1, series corresponds to semiconductors and other electronic component manufacturing. In panel 2, products are classified according to the NIPA classification. NIPA = national income and product accounts. PCE = personal consumption expenditures.

6 Krolikowski and Naggert (2021) reach similar conclusions. Namely that semiconductors shortages and their effects on new car prices will subside within the next six to nine months.

7 Advanced economies include Austria, Belgium, Canada, Switzerland, Czech Republic, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Hong Kong SAR, Ireland, Israel, Italy, Japan, Korea, Lithuania, Latvia, Netherlands, Norway, Portugal, Singapore, Slovak Republic, Slovenia, Sweden and the United States.

8 Ramey (2016) contains a helpful discussion on the relation between reduced form VAR and structural interpretations of coefficients implicit in the above Cholesky ordering.

9 Lopez-Salido and Loria (2020) estimate quantile local projections instead of quantile VAR.

For emerging markets and developing economies, we rely on a dynamic panel version of Eq. (2.4.1):[10]

$$\mathbb{Q}^{\tau}\left(Y_{i,t+1} \middle| Y_{i,t}\right) = \mu_i^{\tau} + \delta_1^{\tau} Y_{i,t+1} + \sum_{s=0}^{S} \delta_{-s}^{\tau} Y_{i,t-s},$$

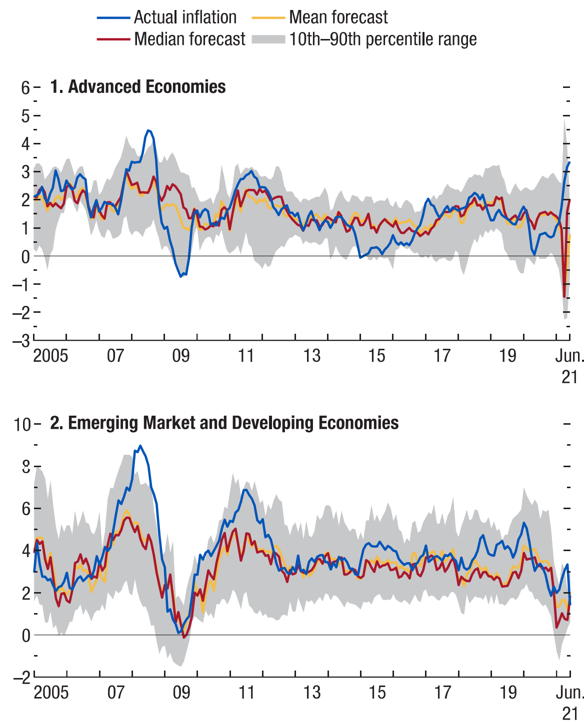
where μ_i^{τ} denotes the country fixed effect for country i in the estimation of conditional quantile τ. This allows us to expand the estimation to many more countries with shorter time series and where single-country VAR estimation is not possible.[11] While we estimate common coefficients across countries (except for the quantile-specific country fixed effects), we proceed with country-specific recursive simulations where initial conditions differ across countries. In all equations, we allow up to 3-month lags.

To assess the fit of the model, we report below the in-sample 12-month ahead headline inflation forecast for AEs and EMDEs separately (Annex Figure 2.4.3). The correlation between actual and mean (median) forecast inflation is 0.53 (0.51) for AEs. Actual inflation exceeds the 10-90 interquantile range in 7 percent of monthly observations in the average sample in AEs, which is lower than the population coverage range of 20 percent.[12] The correlation between actual and mean (median) forecast inflation is 0.73 (0.73) for EMDEs, with 7 percent of monthly observations falling outside the 10-90 predictive interquantile range. While the central tendency forecasts usually fail to predict extreme realizations of inflation—which is to be expected in any linear model—it is reassuring to find that the 10-90th percentile range in Annex Figure 2.4.3 typically increases in periods of high headline inflation volatility. This indicates that the quantile regression approach is useful in predicting the balance of risks to the inflation outlook.

Annex Figure 2.4.3. Headline Inflation In-Sample Fit

(Percent)

The VAR model exhibits a good prediction fit for headline inflation for both advanced economies and emerging market and developing economies.



Source: IMF staff estimates.
Note: Figure shows actual and 12-month ahead predicted inflation for advanced economies. Lines are averages weighted by countries' purchasing-power-parity GDP. VAR = vector autoregression. See Online Annex 2.1 for further details about the list of countries used in the sample.

For each of the 7 endogenous variables, we estimate individual conditional quantiles from 1 to 99. Because there is no analytical solution for the predictive distribution beyond the next period, we rely on the following algorithm to build recursive medium-term inflation forecasts:

[10] Emerging markets and developing economies include Bulgaria, Chile, China, Colombia, Ecuador, Egypt, Hungary, Mexico, Malaysia, Pakistan, Philippines, Poland, Russia, Thailand, Turkey, Ukraine, Uruguay, Vietnam and South Africa. We replace the unemployment rate with the year-on-year change in industrial production, which tracks business cycles better in this group of countries.

[11] We also include Estonia, Israel and Singapore in the dynamic panel estimation. However, these three countries are included in Advanced Economies aggregates when building forecast scenarios. In the case of Mexico, we rely on a single-country VAR but include the forecasting results in the EMDE group.

[12] Comparison of these goodness-of-fit measures with the literature is difficult as most studies do not report such summary statistics.

For each simulation $n = 1, \dots, 1000$:

For each variable (in order) $i \in \{\text{nrg}, \text{food}, \text{extern}, \text{unemp}, \text{disper}, \text{expect}, \text{infl}\}$ in every forecast period $h = 1, \dots, H$:

1. Predict next period quantiles of variable i based on the last observation or forecast available and coefficient estimates from Eq. (2.4.1). Rearrange to produce monotone quantile curves (Chernozhukov, Fernández-Val and Galichon 2010).
2. Drawing from a uniform distribution, randomly select a quantile from 1 to 99.
3. Assign the selected conditional quantile as the realization of variable i in the next period.

End.

End.

Country-specific forecasts are summarized by taking the mean, median and interquantile ranges over the 1000 simulations for the H forecast months.

Country groups require one more level of simulation.

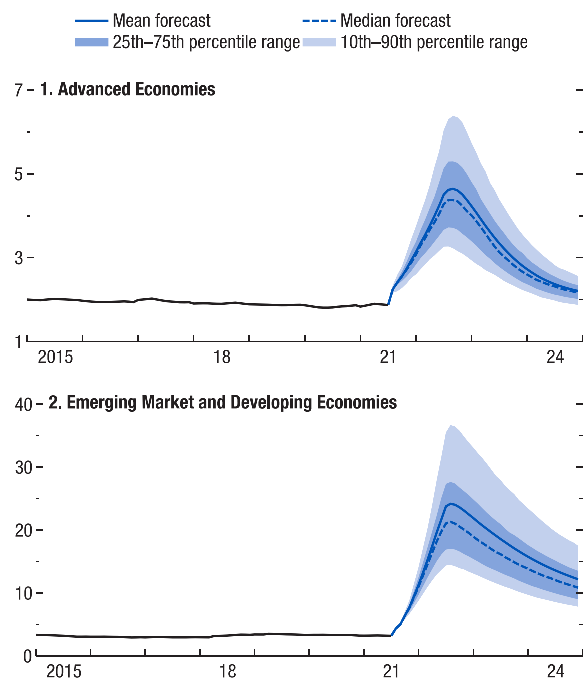
For each simulation $n = 1, \dots, 1000$:

1. For each country in the group, randomly select one simulation forecast path.
2. Calculate the weighted average across all countries using global GDP shares in PPP terms.

End.

Country-group forecasts are summarized by taking the mean, median and interquantile ranges over the 1000 simulations for the H forecast months.

Annex Figure 2.4.4. Inflation Expectations With Adverse Sectoral and Commodity Price Shocks
(Percent)



Sources: Consensus Economics; Haver Analytics; IMF, CPI database; and IMF staff calculations.
Note: Lines are averages weighted by countries' purchasing-power-parity GDP. Adaptive expectations assume that inflation is driven by the one-year ahead inflation expectations instead of the conventional three-year ahead horizon for 12 consecutive months from July 2021 to June 2022. See Online Annex 2.1 for further details about the list of countries included in the samples.

The chapter presents inflation forecasts for a scenario where the extreme sectoral price shock is combined with a scenario in which expectations become adaptive for 12 consecutive months between July 2021 and June 2022.[13] Figure 2.4.4 reports the forecasts for inflation expectations in such a scenario. Expectations increase on average compared to the baseline forecast, with the peak reaching 4 percent in AEs compared to 2 percent in the baseline and 20 percent in EMDEs compared to a peak of 4 percent in the baseline.

[13] This is modeled by replacing the 3-year ahead inflation forecast in the VAR with the 1-year ahead inflation forecast from Consensus Forecasts for 12 consecutive months in AEs. For EMDES, we replace inflation expectations with last month's inflation.