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Inflation at risk in advanced and emerging market economies♥

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Abstract

Using quantile regression techniques, we study the drivers of inflation risks in a large panel of advanced and emerging market economies (EMEs). We document several facts regarding the inflation forecast distribution and highlight some key differences between these two groups of countries. First, the exchange rate has a quantitatively important and non-linear impact on the inflation outlook in EMEs: a depreciation is associated with larger increases in the upper quantiles than in the lower quantiles, increasing the right skewness of the distribution. By contrast, there is no evidence of such non-linearities for advanced economies. Second, tighter financial conditions in EMEs carry both downside and upside risks to inflation, while having a muted impact on the modal or mean outcome. This is in contrast to advanced economies, where only downside risks prove sensitive. Third, the zero lower bound on policy rates translates into substantial downside risks to inflation. Finally, the adoption of inflation targeting is associated not only with lower mean inflation but also with a less right-skewed distribution. Our findings underscore the importance of including non-linearities in structural models of inflation dynamics.

Keywords: quantile regressions; forecast density; inflation risk; monetary policy framework; exchange rates; zero lower bound; inflation targeting.

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1. Introduction

Discussion of inflation risks, especially whether risks to future inflation are balanced or tilted to the upside or downside, often take centre stage in central bank policy meetings and communication. Not only do policymakers consider the most likely future path of inflation, but they also take into account the distribution of outcomes around that path. And following a risk management approach to monetary policy, they may take actions to reduce the probability of extreme inflation outcomes, even if these may not be warranted by the central tendency (see eg Greenspan (2004); Kilian and Manganelli (2008)).

This notwithstanding, research on how to measure inflation risks and the factors that drive them is still very limited. Until recently, the main focus of the academic literature has been on the variance of inflation and its determinants (see eg Engle (1983); Ball and Cecchetti (1990); Grier and Perry (1998)), with little attention being paid on modelling asymmetries and/or thicker tails in the distribution of future inflation. Indeed, a common approach at central banks for assessing or communicating inflation risks is to make assumptions about the distribution of the forecast errors and then to build a density function or a confidence interval around a point forecast, usually generated as the conditional mean from an empirical or structural linear model.[1]

A few empirical studies have analysed the density forecast of future inflation without resorting to restrictive assumptions about its distribution. In an early study, Cecchetti (2008) showed that equity and house price booms asymmetrically affect upside and downside risks to the price level. More recent studies focus on the United States and/or the euro area, drawing on surveys of professional forecasters (eg Andrade et al (2015)) or applying quantile regression techniques (Busetti et al (2015, 2021); Ghysels et al (2018); Korobilis et al (2021); Lopez-Salido and Loria (2022); Tagliabracci (2020)). These studies show the existence of significant

1 Forecast errors are often assumed to be Gaussian, and the forecast error variance is usually proxied by the variance of the in-sample fitted errors. Construction of asymmetric forecast distributions (often in the form of “fan charts”) is also commonplace at central banks. However, asymmetry is usually obtained in an ad-hoc way and relying on judgement (see eg Razi and Loke (2017)).

time variation in the shape of the inflation forecast distribution, which cannot be captured only by changes in the variance of inflation.

In this paper, we extend this nascent literature in two ways. First, unlike the above-mentioned studies, we consider a large panel of advanced and emerging market (EM) economies. The analysis is conducted using a novel method for estimating quantile panel regressions with fixed effects (Machado and Santos Silva (2019)). The panel dimension is particularly valuable in that it increases statistical power, especially when studying EM economies, many of which lack long time series. Second, we uncover several new facts about the factors that drive inflation risks, which to the best of our knowledge have not been documented elsewhere. These facts highlight important differences between advanced and EM economies and provide useful clues as to what non-linearities in inflation dynamics structural models of inflation should try to replicate. In what follows we describe our econometric method and our main findings in detail.

Our quantile panel regressions are based on an open-economy Phillips curve that relates the future inflation quantiles to output, current inflation and changes in the exchange rate and oil prices. In our baseline model, the dependent variable is one-year-ahead inflation, but we also consider longer horizons in our extensions. The estimation is carried out with quarterly data over the period 1990–2019 and is separate for advanced and EM economies, given the significant heterogeneity between these groups of countries. In extensions to the baseline model, we also consider the role of financial conditions (as proxied by realised volatility of stock returns) for future inflation risks.[2] This is motivated by the findings in Lopez-Salido and Loria (2022) that tighter financial conditions are associated with greater downside inflation risks in the United States and the euro area. Finally, we also augment the baseline model with variables that capture important aspects of monetary policy, namely the influence of formal inflation targeting frameworks (eg de Gregorio (2019); Mishkin (2005)) and the zero lower bound constraint on policy interest rates (eg Williams (2014); Bernanke (2017)).

[2] Given the data limitations related to constructing a financial condition index for a large panel of EM economies, financial conditions are proxied by realised equity return volatility. In standard least square panel regressions, the estimated coefficient on this variable is small and statistically insignificant. Its role in affecting inflation risks would therefore not be evident without resorting to quantile regressions.

Importantly, our estimation framework yields the entire distribution of future inflation. Specifically, after estimating the panel quantile regressions using the estimators by Machado and Santos Silva (2019), we compute conditional forecasts of various quantiles of future inflation. These are then interpolated using a flexible density function (such as in the seminal study by Adrian et al (2019) on GDP growth-at-risk). We can thus investigate whether the effects of various risk factors on inflation are non-linear – that is, whether they vary across the quantiles of the conditional inflation forecast distribution.[3] In addition, the distributions allow us to construct measures of downside and upside inflation risks and evaluate their behaviour over time. It is important to note that our aim is not to test causal relationships but to find out how the inflation outlook, including tail risks, responds to typical macroeconomic factors.[4]

The advantage of the quantile regression method is that it is flexible in fitting the conditional distribution of inflation with relatively few parametric assumptions. As we show in this paper, this flexibility can help to better fit tail risks, ie the left and right tails of the inflation forecast distribution, compared with estimating the same model using standard ordinary least squares panel regressions. Our method also links time-variation of the conditional forecast distribution to the dependent variables. Indeed, the usefulness of quantile regression methods in capturing conditional distributions and linking them to time-variation in the dependent variables has seen the application of quantile regressions extended to other standard dynamic models such as VARs (White et al (2015)) and local projections (Han et al (2022)).

Our analysis uncovers several facts about how the variables in our open-economy Phillips curve influence the inflation forecast distribution. These are summarised in Table 1. We find that in both advanced and emerging economies, higher current inflation is associated with an increase in the right skewness of the inflation forecast distribution. The larger and non-linear effects of inflation in the upper quantiles may arise from prices being adjusted more frequently, and with a higher elasticity with respect to current inflation, at higher inflation rates,

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[3] This type of non-linearity differs from other concepts of non-linearities examined in the literature. For example, Gross and Semmler (2019) use a regime-switching model and show that the coefficient on the output gap in the euro area Phillips curve is larger during expansions. Forbes et al (2021) document that the Phillips curve becomes non-linear when inflation is low, with a steep slope during times when output is above potential.

[4] Being largely a forecasting exercise that does not establish causality, our analysis differs from studies such as eg Forbes et al (2018) and Osorio and Unsal (2013), which examine the effects of well-defined shocks to demand, supply or monetary policy on inflation.

than at near-zero inflation rates (eg Alvarez et al (2019)). We also find that weaker GDP growth is associated with a more left-skewed inflation forecast distribution. This is consistent with Nakamura and Steinsson (2011) who postulate that firms keep prices rigid in “normal times” but may apply steep discounts when firm demand is sufficiently low. Although an increase in oil prices shifts the inflation forecast distribution to the right, its influence on the distribution is linear, having no additional effect on the distribution’s skew. This absence of non-linearity in the impact of oil price changes on the inflation forecast distribution is consistent with Wong (2015) – the author finds that while oil prices have a first-round effect on inflation via the cost channel, they have limited second-round effects via the impact of higher inflation on wage and price setting behaviour.

Variable	Advanced economies	Emerging market economies
Inflation	Non-linear: high inflation results in a more right-skewed inflation forecast distribution in addition to a rightward shift in the distribution	Non-linear: high inflation results in a more right-skewed inflation forecast distribution in addition to a rightward shift in the distribution
Log change real GDP	Non-linear: lower GDP growth results in a more left-skewed inflation forecast distribution in addition to a leftward shift in the distribution	Non-linear: lower GDP growth results in a more left-skewed inflation forecast distribution in addition to a leftward shift in the distribution
Log change oil price	Linear: increase in oil prices results in a rightward shift in the inflation forecast distribution but with no change in skew	Linear: increase in oil prices results in a rightward shift in the inflation forecast distribution but with no change in skew
Log change nominal effective exchange rate	Linear: exchange rate depreciation results in a rightward shift in the inflation forecast distribution but no change in the skew	Non-linear: exchange rate depreciation results in a more right-skewed inflation forecast distribution in addition to a rightward shift in the distribution
Financial conditions (realised equity return volatility)	Non-linear: tighter financial conditions result in a more left-skewed inflation forecast distribution in addition to a leftward shift in the distribution	Non-linear: tighter financial conditions result in an outward shift of both the left and right tail of the inflation forecast distribution without shifting the location of the distribution

Table 1: Influence of explanatory variables on the shape of the inflation forecast distribution

Importantly, we find that the *exchange rate* is a powerful source of non-linearity for EM inflation risks: depreciations tend to be related to larger changes in the upper quantiles of the inflation distribution than in the lower quantiles – that is, they tend to increase the right-side skewness of the distribution. The results could stem from greater exchange rate pass-through in emerging markets compared with advanced economies (eg Jasova et al (2019)). Moreover, if firms expect exchange rate shocks to be more persistent when inflation is high, their price setting may be more responsive to exchange rate fluctuations (see Taylor (2000)). By contrast, we do not find evidence of such non-linearities for advanced economies. These results contribute to explaining the prominence of the exchange rate in EME central bank policy frameworks (see Agénor and Pereira da Silva (2019); BIS (2019)) as well as their generally lower importance in advanced economy frameworks.

Extensions to our baseline analysis uncover several additional facts about the inflation forecast distribution. First, we find that *tighter financial conditions in emerging markets* are associated with an increase in *both* upside and downside inflation risks and no significant changes in the conditional mean of inflation; moreover, changes in the tails are almost symmetric. That is, both the left and the right tails of the inflation distribution move outwards by an almost similar amount, leaving its location largely unchanged. Such widening of the predictive distribution reflects the possibility that different channels of inflation dynamics could be at play at different times. Specifically, tighter financial conditions may lead to a severe growth slowdown (Adrian et al (2019)), which acts to reduce price pressures. At the same time, however, tighter financial conditions may go in tandem with a large currency depreciation, which would boost imported inflation, and/or an increase in the share of liquidity-constrained firms raising prices to meet their financial obligations (Gilchrist et al (2017)). For advanced economies we find that only the left tail of the inflation distribution is sensitive to tighter financial conditions, thus corroborating the fact documented in Lopez-Salido and Loria (2022) for the United States.

Second, we find evidence that the adoption of *inflation targeting* is associated with a larger decline in the upper quantiles than in the mean or lower quantiles of the distribution. That is, the right skewness of the inflation distribution diminishes relative to non-inflation targeting countries. Together with the non-linear relationship between the level of inflation and the forecast distribution, this explains why the disinflation process that took place in many advanced and EM economies during the 1990s and early 2000s went hand in hand with ever narrower and ever less skewed forecast distributions.

Finally, our results also show that at low inflation rates the *zero lower bound* has become a relevant source of non-linear inflation risks to the downside, with the effect on the lower tail twice as large as that on the mean. This is consistent with Mertens and Williams (2021), who show that the presence of the lower bound skews the distribution of inflation to the left in a New Keynesian model.

Our findings are robust to several robustness tests and extensions, including different measures of economic activity, commodity prices and exchange rates, the use of inflation expectations as well as the inclusion of various structural factors such as demographics, market power, trade and financial openness.

One interesting application that helps validate the inflation-at-risk model is a comparison with predictions obtained from option prices about deflation risks. Using options data for the United States and the euro area since 2010, we find that options-implied deflation risks are well tracked by the deflation probabilities obtained from our model. Moreover, the difference between the options and model-implied deflation probabilities – a measure of the deflation risk premium – is strongly positively correlated with bond returns and strongly negatively correlated with equity returns. This is consistent with the deflation risk premium driving the observed bond-equity correlations (Campbell et al (2020)).

Finally, we use the inflation-at-risk model to analyse the post Covid-19 inflation surge.

Related literature. Our paper is related to various strands of the literature. A small number of empirical studies have recently quantified inflation risks (asymmetry and tails), yet most focus on the euro area or the United States. For example, Busetti et al (2015) find that the effects of lagged inflation and the exchange rate are not uniform across quantiles in the euro area, while Busetti et al (2021) document that the non-linear relationship between the output gap and the euro area inflation forecast distribution is time varying. Ghysels et al (2018) consider the forecasting performance of quantile inflation risk models with mixed frequency data for the United States, while Korobilis et al (2021) examine the forecasting performance of time-varying quantile regressions for euro area inflation. In a paper concurrent to ours, Lopez-Salido and Loria (2022) document notable variability in the conditional distribution of inflation in the United States and the euro area and show that tighter financial conditions are important contributors to low-inflation risks. In another concurrent paper to ours, Tagliabracci (2020) documents that in Italy downside risks to the conditional distribution of inflation are larger in business cycle downturns while upside risks are more independent of the business cycle. Among earlier studies, Cecchetti (2008) constructs measures of price-at-risk to assess the potential costs of an equity and real estate crash and finds that equity price busts increase downside price risks. Kilian and Manganelli (2007) develop measures of deflation risks linked to private sector preferences, finding that unlike Japan, there was little evidence of deflation risk in the US and the euro area in 2002.

In contrast to the previous literature, by using novel panel quantile methods to pool information on inflation risks across countries, we can examine a number of additional dimensions not analysed in previous studies. We contribute to the literature by examining inflation risks in EMEs where individual time series data tend to be shorter. We find that the exchange rate is an important source of inflation risks, in contrast to advanced economies. We also show that tighter financial conditions increase both up and downside inflation risks in EMEs, in contrast to advanced economies where they tend to only be associated with greater downside risks. By pooling data across countries we are also better able to analyse the types of monetary policy regimes that reduce inflation risks and the extent to which the zero lower bound increases downside inflation risks.

Our paper is also related to the broad literature examining cyclical and structural factors influencing inflation, although unlike our study, this literature overwhelmingly focuses on the conditional mean of inflation. Cyclical factors include the influence of the level of inflation (Alvarez et al (2019)); firms' liquidity constraints (Gilchrist et al (2017)); demand conditions (Nakamura and Steinsson (2011)); the persistence of exchange rate shocks (Taylor (2000)); and global inflation, global slack and global value chains (Ciccarelli and Mojon (2010), Auer et al (2017) and Forbes (2019)). Structural factors include the influence of globalisation and technology (Andrews et al (2018)), Calligaris et (2018)); shifts in market power (De Loecker et al (2020)), or demographics (Juselius and Takáts (2021)). Rogoff (2003) anticipated most of these studies, examining different contributions of central bank independence, demand, technology, and increased competition and globalisation on inflation. Our key findings on the macroeconomic factors influencing inflation risk are robust to the inclusion of these cyclical and structural factors.

The rest of this paper is structured as follows. The next section describes the methodology, together with the data that are used in the empirical analysis. Section 3 contains the baseline estimations from the quantile regressions based on Phillips curves, as well as augmented models that incorporate factors related to monetary policy. Section 4 uses the previous estimates to construct measures of upside and downside inflation risks and discusses their developments over time. Section 5 presents robustness tests, while Section 6 considers some extensions and further applications of the model. Section 7 concludes.

2. Methodology and data

We use quantile panel regressions with fixed effects to estimate the conditional quantiles of the four-quarter-ahead headline inflation rate $Q_{\pi}(\tau|X)$. Specifically, following Machado and Santos Silva (2019), we consider the following location-scale model:

$$\pi_{i,t+4} = \alpha_i + X_{it}'\beta + (\delta_i + X_{it}'\gamma)U_{it}, \qquad (1)$$

where the dependent variable is four-quarter-ahead year-on-year CPI inflation.[5] The vector $X_{it} = (\hat{y}_{i,t}, \pi_{i,t}, \Delta exc_{i,t}, \Delta oil_{i,t})$ in (1) is comprised of explanatory variables in an open-economy Phillips curve for economy i: $\hat{y}_{i,t}$ is a measure of output (either real GDP growth or the output gap), $\pi_{i,t}$ is current inflation, $\Delta exc_{i,t}$ is the change in the exchange rate (nominal effective exchange rate or the US dollar) and $\Delta oil_{i,t}$ denotes the change in oil price in domestic currency. All variables except headline inflation are in logarithms and multiplied by 100.[6]

The parameters $(\alpha_i, \delta_i), i = 1, \ldots, n,$ denote the individual i fixed effects, and $\Pr[\delta_i + X_{it}'\gamma > 0] = 1$. The sequence $\{X_{it}\}$ is assumed to be strictly exogenous, i.i.d. for any fixed *i* and independent across *i*. The U_{it} are unobserved random variables, i.i.d. (across both *i* and *t*), independent of X_{it} and normalised to satisfy $E(U) = 0$ and $E(|U|) = 1$.

The conditional quantiles for four-quarter-ahead inflation are obtained as

$$Q_\pi(\tau|X_{it}) = \big(\alpha_i + \delta_i q(\tau)\big) + X_{it}'\beta + X_{it}'\gamma q(\tau), \qquad (2)$$

where the scalar coefficient $\alpha_i(\tau) \equiv \alpha_i + \delta_i q(\tau)$ is the quantile-τ fixed effect for economy *i*. This captures time-invariant country characteristics that may have different effects in different parts of the conditional inflation distribution, similarly to the other explanatory variables in a quantile regression set-up. We estimate coefficients for five quantiles: the 5, 25, 50, 75 and 95 percent quantiles. The confidence intervals are computed by block bootstrapping using country clusters, with 1,000 replications.

Each predicted quantile in the equation above corresponds to a point in the *cdf* F(.) of the four-quarter-ahead inflation forecast, for each country and quarter. These points can be interpolated to obtain a smooth distribution with which we can carry out risk analysis. Smoothing is also needed because quantile predictions are often noisy, given the error associated with the estimation. In our case, we interpolate semiparametrically the predicted

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[5] Retail price inflation (RPI) is used for the UK until end-2004 and CPI inflation thereafter, reflecting the change in the inflation target. Separate cross-sections are included in the estimation for United Kingdom pre- and post-2005.

[6] While we estimate separate models for AEs and EMEs, we assume equal slope coefficients within these two groups of countries. Thus, we do not consider different degrees of non-linearities within AEs and EMEs, stemming for example from differences in wage and price rigidities across economies.

quantiles using the skewed *t*-distribution to take advantage of its overall shape flexibility (see Azzalini and Capitanio (2003)). The distribution is described by the following function:

$$f(\pi;\mu,\sigma,\alpha,v)=\frac{2}{\sigma}t\left(\frac{\pi-\mu}{\sigma};v\right)T\left(\alpha\frac{\pi-\mu}{\sigma}\sqrt{\frac{v+1}{v+\left(\frac{\pi-\mu}{\sigma}\right)^2}};v+1\right), \qquad (3)$$

where *t(.)* and *T(.)* are the *pdf* and the *cdf* of the distribution, respectively. The four parameters that control the location (μ), scale (σ), fatness (v) and shape (α) of the distribution can be computed for each set of observations corresponding to a pair (country; quarter) to minimise the distance between the five estimated quantiles and those implied by the distribution, ie:

$$(\hat{\mu}_{it+h},\hat{\sigma}_{it+h},\hat{\alpha}_{it+h},\hat{v}_{it+h})=argmin\sum\nolimits_{\tau}\left(\hat{Q}_{\pi_{t+h}|x_t}(\tau|x_t)-F^{-1}(\tau;\mu,\sigma,\alpha,v)\right)^2. \qquad (4)$$

Our data cover 43 economies, 12 advanced economies (AEs) and 31 EMEs.[7] The sample runs from Q1 1990 to Q1 2019 for all advanced economies and 17 EMEs. For the remaining 14 EMEs – Argentina and countries in central and eastern Europe – the sample starts between 1993 and 1997, based on data availability. To deal with outlier observations, we exclude all quarters where both four-quarter-ahead inflation and current inflation are above 50%.[8] Panel unit root tests do not suggest concerns about stationarity over the estimation sample.[9] Annex Table A1 shows details about the data sources.

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7 The advanced economies are Canada, France, Germany, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, the United Kingdom and the United States. The EMEs are Argentina, Brazil, Bulgaria, Chile, China, Chinese Taipei, Colombia, Croatia, the Czech Republic, Estonia, Hong Kong SAR, Hungary, India, Indonesia, Korea, Latvia, Lithuania, Malaysia, Mexico, Peru, the Philippines, Poland, Romania, Russia, Singapore, Slovenia, Slovakia, Thailand, Turkey, Ukraine and Venezuela.

8 Although quantile methods are more robust to outliers compared with least squares methods (see eg Machado and Santos Silva (2019)), they are not immune to distortions from extreme outliers. Thus, we exclude the very high inflation rates in our sample as they result in large distortions to our EME estimates even at the lowest inflation quantiles.

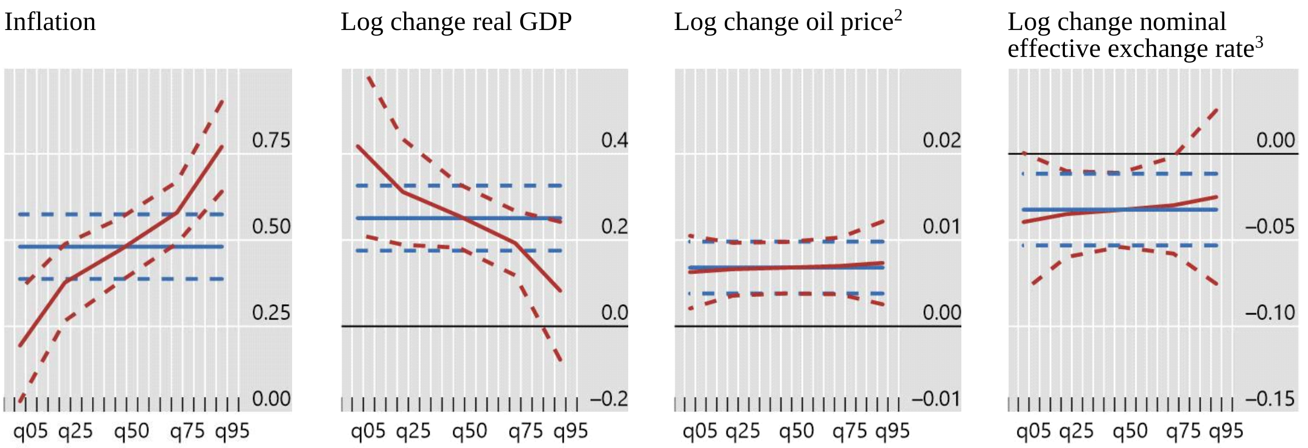
9 Specifically, the Im-Pesaran-Shin (2003) test suggests that the null hypothesis of unit roots is rejected for the variables included in the estimated Phillips curve at the 1% level: inflation, log change in real GDP, log change in oil price and log change in the nominal effective exchange rate.

3. Baseline results

3.1 Estimated quantile regressions

Graph 1 shows the coefficient estimates from the quantile regressions for advanced economies, at the 5, 25, 50, 75 and 95 percent quantiles (red line), together with the least squares estimate (blue line). At these quantiles, the four-quarter-ahead inflation in AEs ranges from –0.3% (5 percent quantile) to 4.5% (95 percent quantile), with a median of 1.8% (see Annex Table A2). The detailed quantile regression estimates are shown in Annex Table A3.

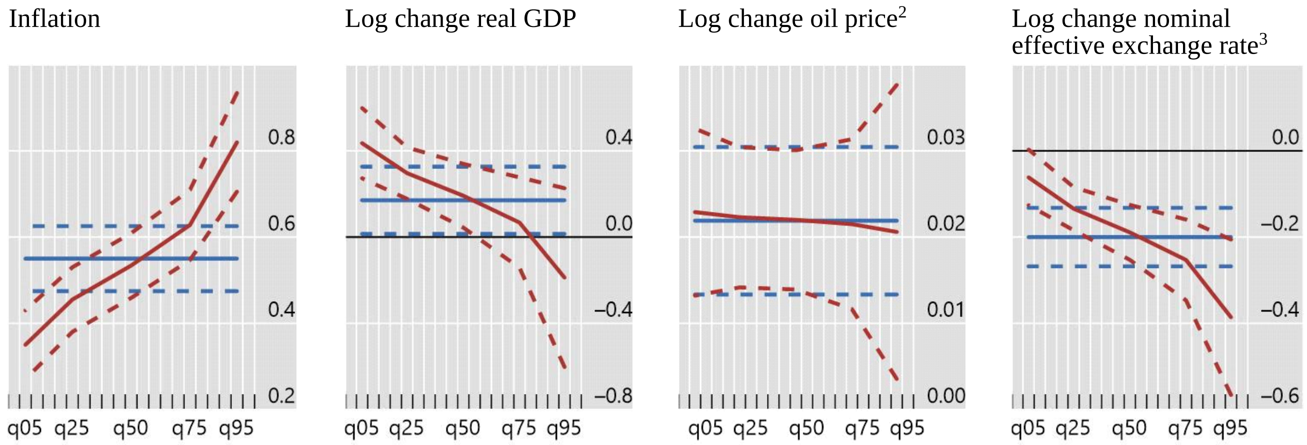
Graph 1 highlights economically and statistically significant nonlinearities associated with both current inflation and output growth. In particular, current inflation affects most strongly the right-hand tail of the inflation forecast distribution, while the effects of output growth are stronger at the left-hand than at the right-hand tail. By contrast, for oil prices and exchange rates, the quantile regression slopes are highly similar to the linear regression slopes. All coefficients in the Phillips curve have the expected signs, including the change in the exchange rate: an exchange rate appreciation is associated with a decline in future inflation.



[1] Estimated coefficients from regressing four-quarter-ahead year-on-year CPI inflation on current inflation, log change in real GDP, log change in the oil price and log change in the nominal effective exchange rate. See equation (1) for details. OLS regressions in blue and quantile regressions in red; 90% confidence intervals. [2] In domestic currency. [3] Increase denotes an appreciation of domestic currency.

Graph 1: Estimated quantile regression and OLS coefficients, advanced economies

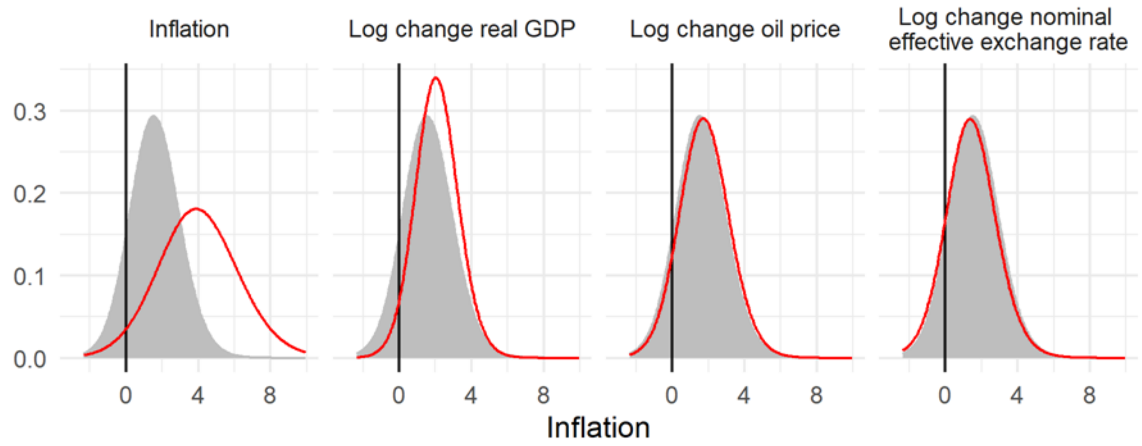
Graph 2 shows the coefficient estimates for EMEs (see also Annex Table A4). While non-linearities and the sizes of the coefficients associated with current inflation and output growth are perhaps surprisingly similar between advanced economies and EMEs, a major difference is the nonlinear effect of the exchange rate. Graph 2 shows that changes in exchange rates have the strongest impact on the right-hand tail of the distribution, whereas the effects are muted at the left-hand tail. Moreover, the least squares coefficient associated with the exchange rate, as well as the median estimate from the quantile regression, is around six times larger in EMEs than in advanced economies. Not surprisingly, the levels of four-quarter-ahead inflation at most quantiles are also higher in EMEs, with a median of 4.0% and the 95 percent quantile at 20.5% (see Annex Table A2).



[1] Estimated coefficients from regressing four-quarter-ahead year-on-year CPI inflation on current inflation, log change in real GDP, log change in the oil price and log change in the nominal effective exchange rate. See equation (1) for details. OLS regressions in blue and quantile regressions in red; 90% confidence intervals. [2] In domestic currency. [3] Increase denotes an appreciation of domestic currency.

Graph 2: Estimated quantile regression and OLS coefficients, EMEs

An alternative way to illustrate the nonlinear effects is to evaluate how changes in the different risk factors affect the conditional distributions. Graph 3 considers the conditional probability density functions for inflation in advanced economies, fitted as skewed *t*-distributions using the quantile regressions and the methodology discussed in Section 2. For the distributions shown in Graph 3, we set all variables to their means, and then change the value of each risk factor by two standard deviations, one variable at a time to examine the economic importance of each factor.



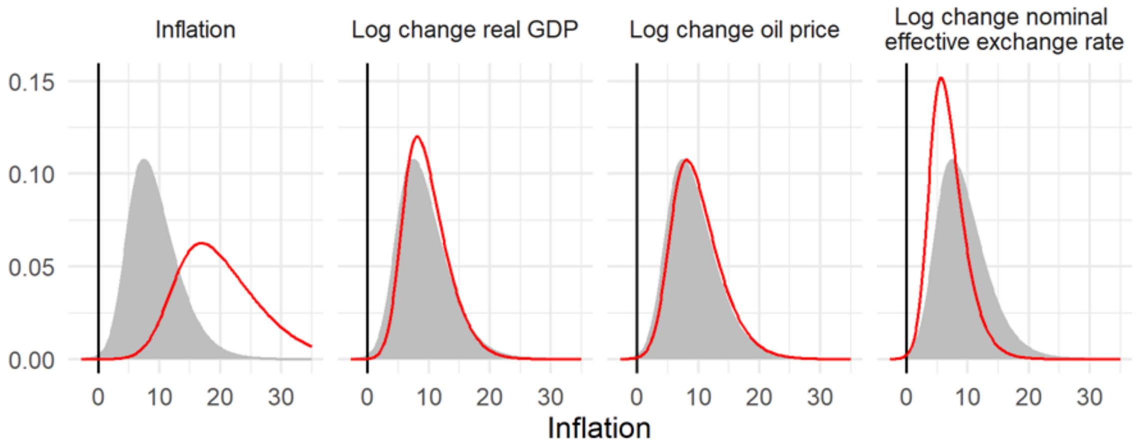
Note: The Graph shows how a two standard deviation increase in the respective variables from its mean affects the conditional inflation forecast distribution (shift from grey to red). For the computation of the distributions, all other variables are set at their means. An increase in the exchange rate denotes an appreciation of domestic currency.

Graph 3: Effect of risk factors on four-quarter-ahead CPI inflation forecast distribution, advanced economies

Graph 3 shows how, in addition to shifting the location of the future inflation distribution, GDP growth and lagged inflation have contrasting implications for the tails of the distribution. In particular, increases in lagged inflation result in distributions with greater positive skewness, as the right-tail is affected by more than the left. In the case of a pick-up in real GDP growth, the left-tail shifts but the right tail remains broadly unchanged. By contrast, changes in oil prices and exchange rates only shift the location of the distribution marginally without any visible effects on the tails.

Graph 4 replicates the analysis for EMEs and highlights how exchange rate appreciations are associated with leftward shifts in the distribution as well as reduced positive skew. Thus, as the exchange rate appreciates, upside risks to inflation decline. Other dynamics are similar to those in advanced economies.

We also highlight the importance of the exchange rate for conditional distributions in EMEs by documenting the shifts occurring around currency crises. Graph 5 shows the probability density functions for four-quarter-ahead inflation, computed four quarters before a currency crisis occurs (blue), as well as during the quarter of the crisis (violet). We consider the Asian crisis episodes for Korea and Thailand, the Tequila crisis in Mexico, and Brazil's financial crisis of the late 1990s. The currency crisis dates are associated with rightward shifts in the location of the density functions. But even more prominently, the distributions widen significantly and upside inflation risks rise for all the economies.



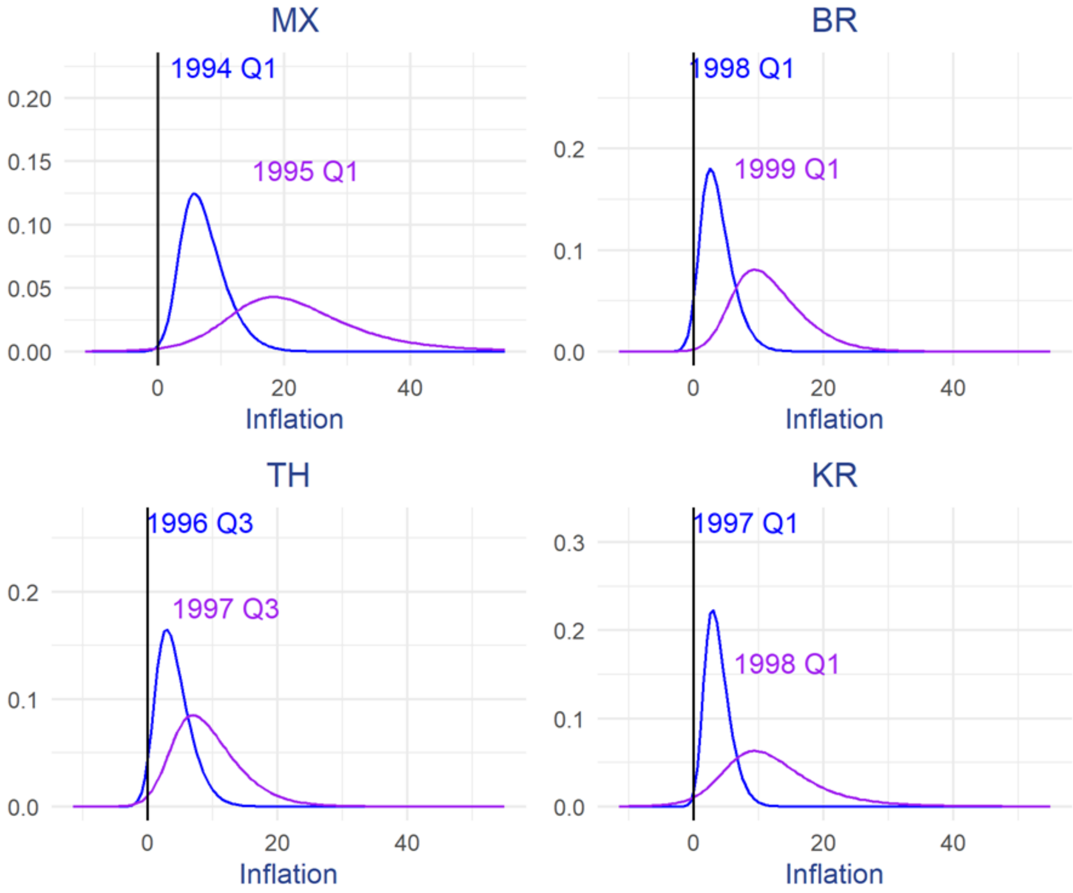
Note: The Graph shows how a two standard deviation increase in the respective variables from its mean affects the conditional inflation forecast distribution (shift from grey to red). For the computation of the distributions, all other variables are set at their means. An increase in the exchange rate denotes an appreciation of domestic currency.

Graph 4: Effect of risk factors on four-quarter-ahead CPI inflation forecast distribution, EMEs

What are the possible economic rationales behind some the observed non-linearities in the Phillips curve? The higher inflation persistence and the larger effects of exchange rate changes in the upper quantiles may partly arise from prices being adjusted more frequently at higher than at near-zero inflation rates (see eg Alvarez et al (2019) for theoretical and empirical evidence), as well as stronger wage-price spirals when future inflation is expected to be high. Another possibility is that firms are more averse to goods being under-priced than over-priced (see Devereux and Siu (2007)), strongly passing through higher costs to prices when they expect high inflation. Moreover, if firms expect exchange rate shocks to be more persistent when inflation is high, their price setting may be more responsive to exchange rate fluctuations (see Taylor (2000)).[10] Finally, the stronger relationship between output growth and inflation at the

[10] An and Wang (2012) report that exchange rate pass-through is greater in economies with more persistent exchange rate shocks.

lower quantiles is consistent with Nakamura and Steinsson (2011) who postulate that firms keep prices rigid in "normal times" but apply steep discounts when firm demand is sufficiently low.



Note: BR = Brazil; KR = Korea; MX = Mexico; TH = Thailand

Graph 5: Forecast densities for four-quarter-ahead CPI inflation one year prior and during currency crises, selected EMEs

3.2 Forecasting performance

The results above show that the quantile regression framework uncovers significant non-linear relationships between variables in the Phillips curve and the conditional forecast distribution of inflation, ie between variables in the Phillips curve and future inflation risks. A key question is whether the inclusion of these non-linearities helps capture true inflation risks. One way to answer this question is to test whether the inclusion of the non-linearities by means of a quantile regression model improves the fit of the conditional forecast distribution of inflation compared to a model that does not account for these non-linearities.

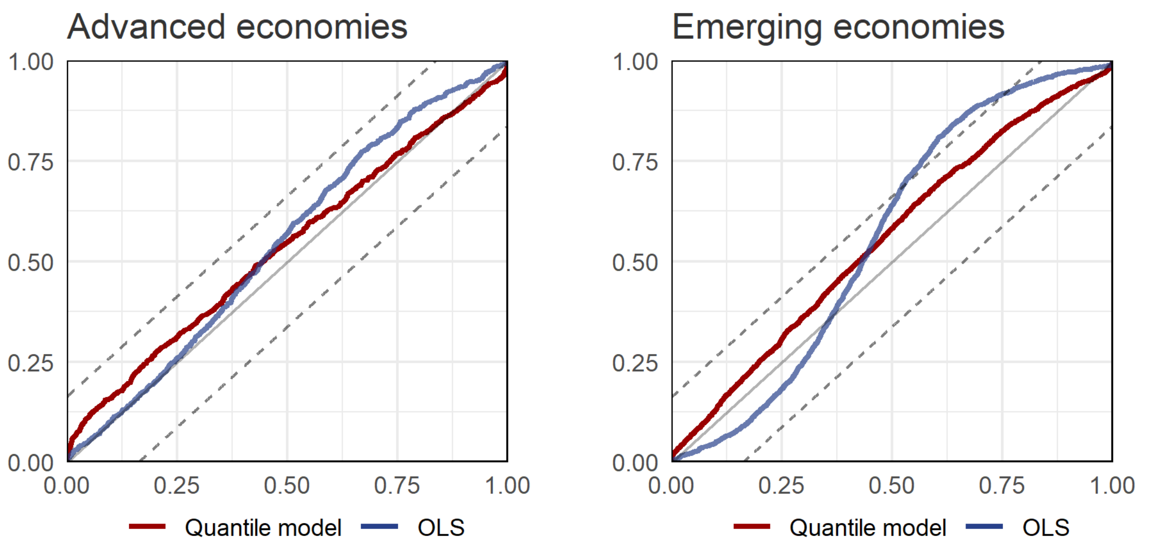
To this end, we evaluate the out-of-sample predictive ability of our model to fit inflation risks. Specifically, we analyse the probability integral transform (PIT), which is in our case the cumulative conditional inflation forecast distribution from the model evaluated at the outturn. We then compute the empirical cumulative distribution of the PITs (see eg Rossi and Sekhposyan (2019)). A comparison of the PIT with its empirical cumulative distribution shows the percentage of inflation outturns that is below a specific quantile of the inflation forecast distribution produced by the model. If a model's conditional forecast distribution of inflation captures the true inflation risk distribution well, then the fraction of inflation outturns below any given quantile, $Q_{\pi}(\tau|X_{it})$ of our model's conditional inflation forecast distribution, should be close to τ. In other words, after evaluating all the quarterly inflation outturns against the model's inflation forecast distribution produced four quarters earlier, 5% of outcomes should have appeared to the left of the 5th percentile of our model's conditional inflation distribution, 10% of outcomes to the left of the 10th percentile of our model's conditional inflation distribution and so on.

To compare the added value of the quantile regression framework, we compare the empirical cumulative distribution of the PIT produced by our baseline quantile panel regression model to the empirical cumulative distribution of the PIT produced by a similarly specified panel OLS regression.[11] We then check how closely the fraction of outcomes is to the quantile produced by either model. The results are shown in Graph 6. Observations close to the 45-degree line would suggest a well calibrated model. Following Rossi and Sekhposyan (2017), we report confidence bands around the 45-degree line to account for sample uncertainty.

Graph 6 (left-hand panel) shows that for advanced economies, both the out-of-sample forecasts from the quantile regression and the OLS model capture inflation risks reasonably well, as they are both close to the 45-degree line and within the confidence bands. At the tails of the distribution there are, however, some differences in the fit of the two models. The non-

[11] The baseline results from the latter model – based on the same explanatory variables – are presented in Graphs 1 and 2.

linearities captured by the quantile model track high inflation outcomes in the right-tail well, shown by the closeness of the PIT to the 45 -degree line. By contrast, the OLS model tends to capture the risk of higher inflation less well. However, for low inflation outcomes in the left-tail, the OLS model appears to perform somewhat better, with the quantile model assigning too much weight to extremely low inflation outcomes.



Note: The x-axis shows the quantile (ie the cumulative inflation forecast distribution evaluated at the inflation outturn four quarters later) and the y-axis the empirical cumulative distribution of the quantiles. The red lines show the probability integral transform in the baseline quantile regression model, while the red lines show the probability integral transform in the baseline model estimated with OLS. 95% critical values are included around the 45-degree line based on Rossi and Sekhposyan (2019).

Graph 6: Cumulative distribution of the probability integral transform from quantile and OLS models

For emerging economies, the out-of-sample analysis suggests that the quantile model appears to better fit the true conditional distribution of inflation compared to the OLS model (right-hand panel of Graph 6). While the empirical cumulative distribution of the quantile model's PIT sits within the 95% confidence bands, that of the OLS model falls outside. The differences in the PITs suggest that the non-linearities accounted for by the quantile model help to better capture the tails of the conditional distribution of inflation in EMEs. By contrast, the OLS model, which does not account for the non-linearities, appears to underweight both downside and upside inflation risks.

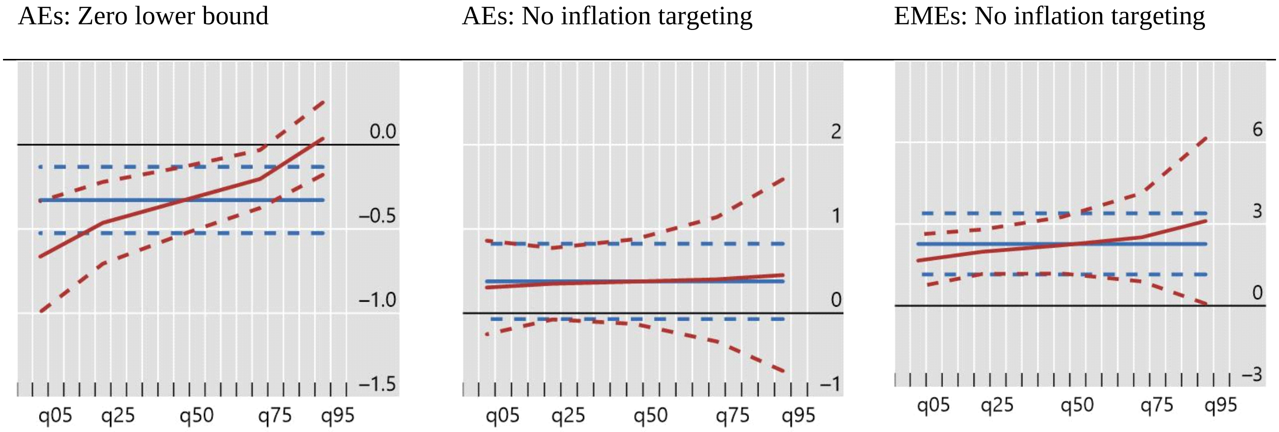
Taken together, these findings suggest that the quantile regression model, by including the non-linearities, better captures the true conditional distribution of inflation than an OLS model, especially for emerging economies.

3.3 Importance of monetary policy

The higher coefficients and nonlinearities observed for the exchange rate in EMEs are consistent with the prominent role of exchange rates in EME policy frameworks. One factor is exchange rate pass-through, which tends to be higher in EM than in advanced economies (see eg Jasova et al (2019) and references therein). Other reasons include the relevance of exchange rate fluctuations for financial stability, as reflected in frequent FX interventions and the increasing use of FX-related macroprudential policies (see BIS (2019) and Im and Pereira da Silva (2019)).

Besides exchange rates, other variables related to monetary policy may also have had a bearing on inflation risks in recent years. Below, we focus on two factors: the zero lower bound (ZLB) in the case of advanced economies, and the possible existence of an inflation targeting framework in both groups of countries. The relevance of the former for inflation risks relates to possible constraints regarding policy space, while the latter could work through the strength of the policy response, and expectations thereof, to inflation.

To investigate the relevance of these factors, we first add a dummy variable for the ZLB in the estimated quantile Phillips curve for advanced economies. The dummy takes a value of one during periods when policy interest rates are at or below 0.5% and zero otherwise. The left-hand panel of Graph 7 shows that being at the ZLB has the largest effect on the left-tail of the inflation distribution, with a coefficient estimate of –0.66 at the 5 percent quantile, compared with –0.33 at the median. The latter estimate is close to that reported by Mertens and Williams (2021) who document a decline in the median long-term inflation forecast during the zero lower bound, based on distributions computed from financial market data for the United States. However, and in addition to the decline in the median, our estimates for a panel of advanced economies suggest prominent nonlinearities associated with the zero lower bound, as the distance between the median and the left tail increases. The left-hand panel of Graph 8 shows the associated shift in the density function.



[1] Estimated coefficients from regressing four-quarter-ahead year-on-year CPI inflation on current inflation, log change in real GDP, log change in the oil price and log change in the nominal effective exchange rate. The regression in the left-hand panel also includes a zero-lower bound dummy, while the centre and right hand panel include dummy variables for country-years when the central bank did not have an inflation target. See equation (1) for details. OLS regressions in blue and quantile regressions in red; 90% confidence intervals.

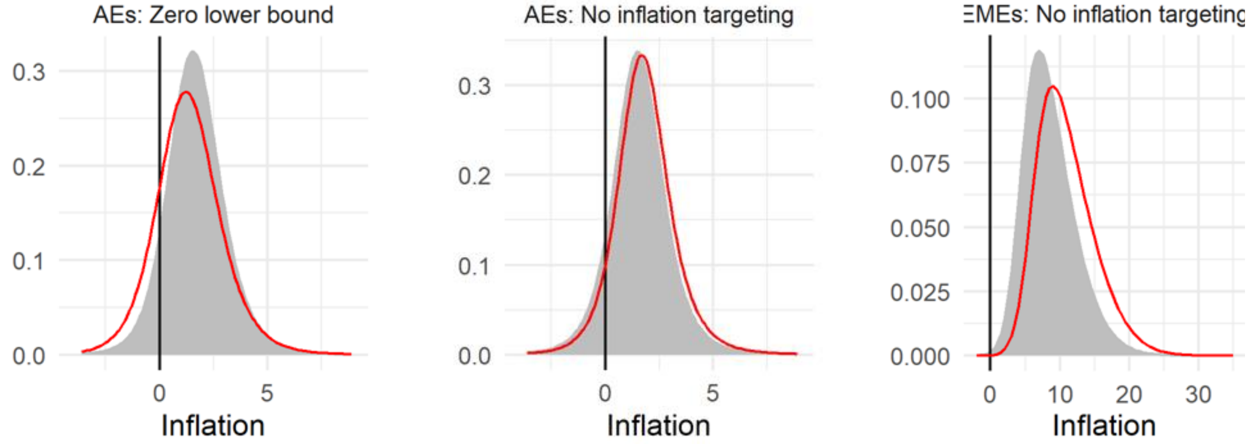
Graph 7: Estimated quantile regression and OLS coefficients for dummy variables for the zero lower bound and when the central bank did not have an inflation target

Second, we consider another variable related to the policy regime in the baseline Phillips curves for both advanced economies and EMEs. This dummy variable obtains a value of one during periods when an economy was *not* pursuing inflation targeting and zero otherwise.[12] For advanced economies, quantile estimations show that the implications of such a variable for future inflation are linear and the OLS estimates are not statistically significantly different from zero (Graph 6, centre panel). Similarly, there is little change in the density function (Graph 8, centre panel).

By contrast, inflation targeting is highly relevant for inflation distributions in EMEs. In particular, not targeting inflation is associated with higher four-quarter-ahead inflation, by around two percentage points on average. Moreover, the effect is nonlinear, as the right tail is affected by more than the left tail (right-hand panel of Graph 7). Note also the much larger scale on the x-axis of the density function in Graph 8 for the non-inflation targeting variable in EMEs than in advanced economies.

[12] The classification of countries into IT and non-IT regimes follows the working paper version of Mehrotra and Yetman (2018). In addition, for some of the recent time periods, we classify Argentina, India, Japan, Russia and the United States as inflation targeters.

Equipped with these results, in the remainder of the paper, all models for advanced economies include the ZLB dummy and the ones for EMEs include the non-IT dummy variable. The corresponding quantile conditional forecasts are shown in Annex Graph A1 for all advanced economies and in Graph A2 for all EMEs in our sample.



Note: The Graph shows how changes in the dummy variables from zero to one affect the conditional inflation forecast distribution (shift from grey to red). For the computation of the distributions, all other variables are set at their means. The left and right-hand panels are based on the Phillips curve estimates shown in Annex Tables A5 and A6, respectively.

Graph 8: Effect of monetary policy-related risk factors on four-quarter-ahead CPI inflation forecast distribution

4. Quantifying inflation risks

We now proceed to evaluate indicators of inflation tail risks. The objective is to examine the likelihood that future inflation is affected by upside or downside risks. We do this by using measures proposed by Adrian et al (2019): downside and upside entropy.[13]

Downside and upside entropy measure the probability mass of left- and right-tail outcomes under the conditional density, relative to the probability of these outcomes under the unconditional density. Thus, they illustrate whether left- or right-tail inflation outcomes are

[13] Two other measures, expected shortfall and the longrise, which measure (average) inflation in the left and right tails of the distribution respectively, provide a qualitatively similar picture of inflation risks. See Graphs A3 and A4 in the Appendix.

more likely under the conditional forecast than under the inflation forecast implied by the unconditional distribution.[14] The unconditional density $\hat{g}_{y_{t+h}}$ is obtained as the unconditional empirical distribution of inflation and is computed from quantile regressions including only the fixed effects as the explanatory variables.

Let $\hat{f}_{\pi_{t+h}}(\pi|x_t) = f(\pi; \hat{\mu}_{t+h}, \hat{\sigma}_{t+h}, \hat{\alpha}_{t+h}, \hat{\vartheta}_{t+h})$ denote the estimated skewed *t*-distribution and $\hat{F}_{\pi_{t+h}}(\pi|x_t)$ the corresponding cumulative distribution. $\hat{F}^{-1}_{\pi_{t+h|x_t}}(0.5|x_t)$ is the conditional median.

The downside Ξ_t^{down} and upside Ξ_t^{up} entropy of $\hat{g}_{\pi_{t+h}}$ relative to $\hat{f}_{\pi_{t+h}}(\pi|x_t)$ are computed as:

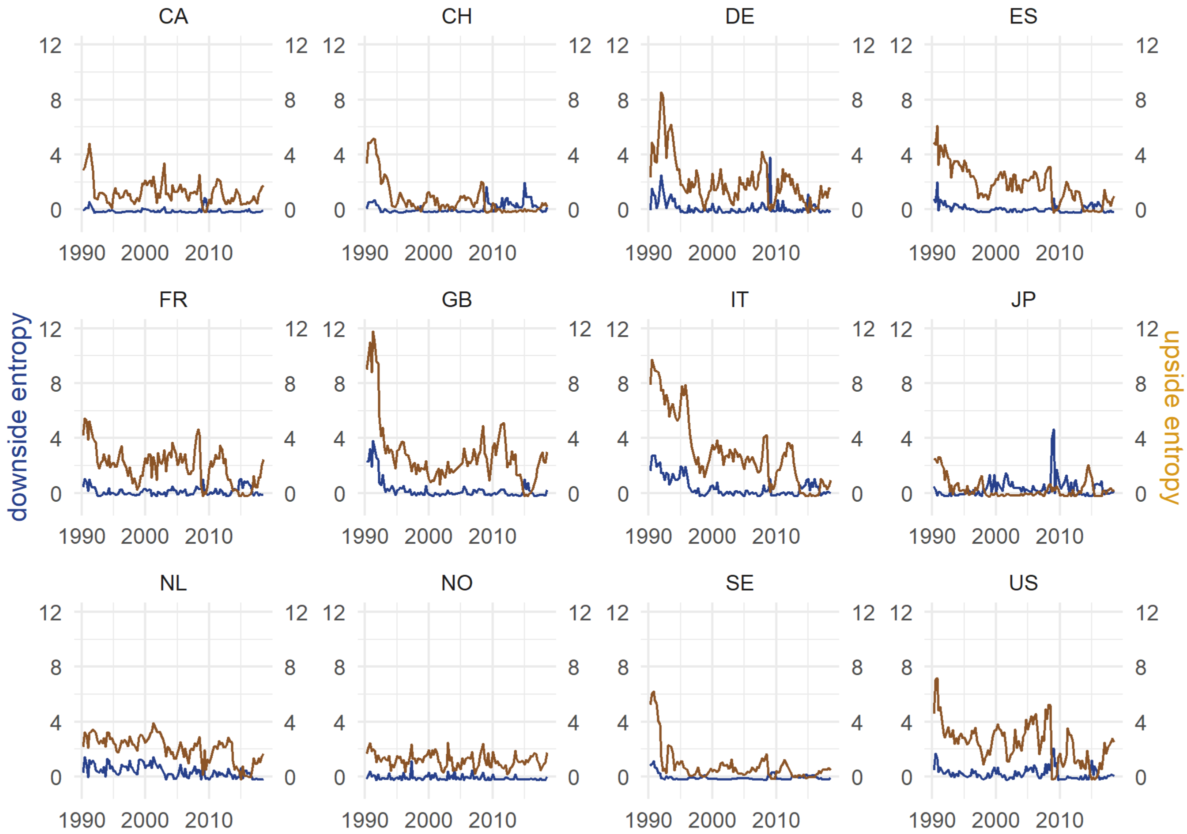
$$\Xi_t^{down}\left(\hat{f}_{\pi_{t+h|x_t}}; \hat{g}_{\pi_{t+h}}\right) = -\int_{-\infty}^{\hat{F}^{-1}_{\pi_{t+h|x_t}}(0.5|x_t)} (\log \hat{g}_{\pi_{t+h}}(\pi) - \log \hat{f}_{\pi_{t+h|x_t}}(\pi|x_t))\hat{f}_{\pi_{t+h|x_t}}(\pi|x_t)\, d\pi \quad (5)$$

$$\Xi_t^{up}\left(\hat{f}_{\pi_{t+h|x_t}}; \hat{g}_{\pi_{t+h}}\right) = -\int_{\hat{F}^{-1}_{\pi_{t+h|x_t}}(0.5|x_t)}^{\infty} (\log \hat{g}_{\pi_{t+h}}(\pi) - \log \hat{f}_{\pi_{t+h|x_t}}(\pi|x_t))\hat{f}_{\pi_{t+h|x_t}}(\pi|x_t)\, d\pi. \quad (6)$$

Thus, downside entropy amounts to the difference between the unconditional density and the conditional density that obtains below the median of the conditional density. And, upside entropy measures the difference between the unconditional density and the conditional density that obtains above the median of the conditional density. These measures are shown in Graphs 9 and 10 for advanced economies and EMEs, respectively.

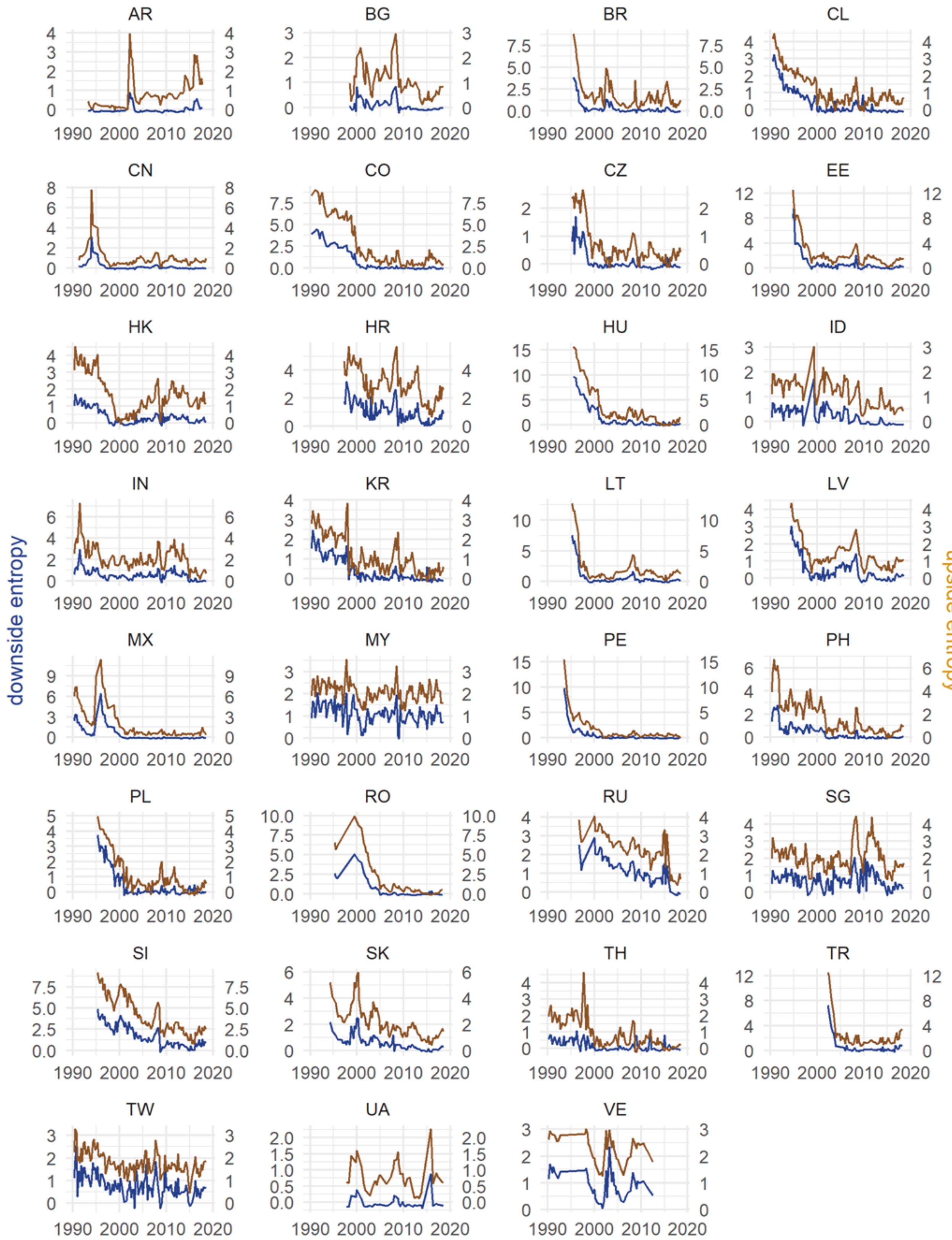
Graph 9 suggests that there is considerably more volatility in upside than in downside risks, as captured by the upside and downside entropy measures. Moreover, most advanced economies have seen a downward trend in upside entropy over time. Therefore, the conditional density has, over time, gradually assigned lower probabilities to extreme right-hand tail inflation outcomes, relative to the unconditional density. However, upside entropy has increased recently in many economies, perhaps most prominently in France and the United Kingdom. As to downside entropy, this measure saw an increase at the time of the Great Financial Crisis, followed in some countries by another pick-up later (eg France, Japan, Switzerland).

[14] As noted by Adrian et al (2019), the upside and downside vulnerability of future inflation is then, on the basis of the entropy measure, the "extra" probability mass that the conditional density yields to upside/downside inflation outcomes compared with the unconditional distribution.



Note: The downside entropy is shown in blue and the upside entropy in yellow. See Graph A1 for country abbreviations.

Graph 9: Inflation risks: downside and upside entropy, advanced economies



Note: The downside entropy is shown in blue and the upside entropy in yellow. See Graph A2 for country abbreviations.

Graph 9: Inflation risks: downside and upside entropy, EMEs

In EMEs, the volatility of upside entropy is also higher than that of downside entropy. Moreover, its longer-term decline tends to be even more pronounced than in the case of advanced economies (Graph 10). The most prominent exception is Argentina, where the level of upside risk has increased over time. Upside risks have spiked during EME crises, as is clear from observations during the financial crises in emerging Asia and Latin America in the late 1990s-early 2000s. Interestingly, these same periods have also seen an increase in downside risks.

Indeed, changes in upside and downside entropy are correlated, and more so in EMEs than in advanced economies (correlation of 0.68 in EMEs vs 0.29 in advanced economies). Moreover, periods of simultaneously rising upside and downside entropy are often associated with large exchange rate depreciations, especially in EMEs. Considering all quarters where exchange rate changes are in the lowest decile, implying a notable weakening of the domestic currency, upside and downside entropy both increased during 58% of observations in EMEs. This compares with a share of 29% in advanced economies.

5. Robustness tests

We conduct four types of robustness tests. First, in section 5.1 we consider other cyclical drivers of inflation risks in the Phillips curve. Second, in section 5.2 we test whether the baseline results are robust to the inclusion of various structural factors in the model. Third, in section 5.3 we estimate the model with alternative dependent variables. Fourth, in section 5.4 we test for structural breaks and estimate the model for shorter sub-samples.

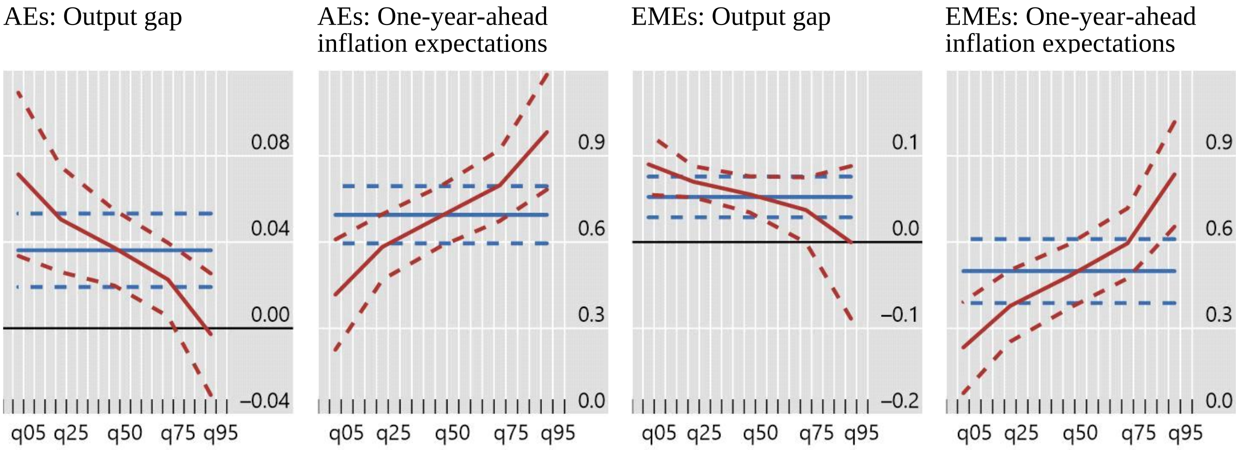
5.1 Other cyclical drivers of inflation

As to other cyclical drivers, we consider alternative measures of economic activity, commodity prices and exchange rates, as well as the importance of inflation expectations.

In order to evaluate whether the Phillips curve estimates are robust to considering a measure of *output gap* instead of real GDP growth, we replace the latter variable by the measure proposed by Hamilton (2018). Here, the output gap is obtained as the residual υ_t from the following linear projection:

$$y_t = \beta_0 + \beta_1 y_{t-8} + \beta_2 y_{t-9} + \beta_3 y_{t-10} + \beta_4 y_{t-11} + \upsilon_t \qquad (7)$$

where y denotes log real GDP.



[1] Estimated coefficients from regressing four-quarter-ahead year-on-year CPI inflation on current inflation, log change in real GDP, log change in the oil price and log change in the nominal effective exchange rate. The first and third panels replace the log change in real GDP with the output gap, the second and fourth panels replace current inflation with one-year-ahead inflation expectations. OLS regressions in blue and quantile regressions in red; 90% confidence intervals.

Graph 11: Estimated quantile regression and OLS coefficients, robustness tests

The nonlinearities associated with the output gap in the Phillips curve are similar to those obtained with real GDP growth (Graph 11, first and third panels). In both advanced economies and EMEs, the output gap has a greater effect on the left than on the right tail of the future inflation distribution.[15] The point estimates, including those from the OLS regressions, are similar in both groups of countries. The other coefficients in the Phillips curve are robust to the inclusion of the output gap.[16]

As an alternative measure of *economic activity*, we estimate the Phillips curve for advanced economies with the unemployment rate. Annex Table A7 shows that, in contrast to the two measures of output, the effects of unemployment are somewhat larger in the right tail of the future inflation distribution, with higher unemployment dampening future inflation. However, the degree of non-linearity tends to be smaller than with the two output-based

[15] This result is different from some of the non-linearities documented in previous literature (eg Busetti et al (2021)). Relatedly, in the wage Phillips curves estimated in Hooper et al (2020), the slope is steeper in tight labour markets.

[16] Detailed results are available from the authors upon request.

measures and the standard errors are relatively wide. We also note that limited data availability precludes the use of the unemployment rate in the EME panel.

Given that a number of papers have highlighted the importance of *global factors* for inflation (eg Borio and Filardo (2007); Ciccarelli and Mojon (2010); Forbes (2019)), we include a measure of global economic activity in the baseline model. This is constructed as a weighted measure of trading partners' GDP growth rates. The weights are based on the size of the country's total trade (imports+exports) with each trading partner country in the sample, computed over three-year windows. Annex Tables A8 and A9 show that the non-linearities associated with global growth are similar to those obtained for domestic GDP growth, with the effect on inflation being higher at the lower quantiles. Moreover, the economic significance of the global activity measure is stronger than that of the domestic one, echoing the findings in Borio and Filardo (2007). The difference is particularly large for EMEs.

Next, we consider other measures of *commodity prices* in the Phillips curve. Not surprisingly, using another measure of global oil prices (Brent instead of WTI) has little effect on the baseline results (Annex Tables A10 and A11). The coefficients on the oil price for advanced economies are slightly higher when using Brent rather than WTI but the differences are small. We also include a measure of global food price inflation as an additional explanatory variable in the model. Annex Tables A12 and A13 show that food price inflation is particularly important for EMEs, where its economic significance is much higher than that of oil prices. The finding regarding the relevance of food prices in EMEs is consistent with Furceri et al (2016). Interestingly, we find that food prices display strong non-linearities with respect to future inflation, raising especially upside headline inflation risks.

We also replace the nominal effective exchange rate by the *bilateral exchange rate against the US dollar*, given the dominance of the US dollar in global trade invoicing and finance (see Gopinath et al (2020)). For EMEs, the resulting estimates show similar non-linearity as with the NEER (Annex Table A15), with the bilateral dollar exchange rate mattering more for inflation in the upper quantiles. For AEs, the coefficient on the US dollar is not statistically significant (Annex Table A14).

As a final alternative cyclical factor, we evaluate the importance of short-term *inflation expectations* in the Phillips curve. Due to data availability considerations in our large panel of economies, we use professional forecasts from Consensus Economics. As the forecasts from Consensus pertain to inflation in the current and next calendar year, we transform these into one-year-ahead forecasts by computing a weighted average of current and next-year forecasts.

This approach has been widely used in the literature (see eg Dovern et al (2012); Siklos (2013)). With h as the forecast horizon, the 12-month-ahead forecast is computed as

$$\hat{\pi}_{t+12|t} = \frac{h}{12}\hat{\pi}_{t+h|t} + \frac{12-h}{12}\hat{\pi}_{t+12+h|t} \tag{8}$$

where $\frac{h}{12}$ and $\frac{12-h}{12}$ denote the weights, ie the shares of current and next-year forecasts in the forecast period. Then, given the high correlation between current inflation and one-year-ahead expectations, especially in advanced economies (0.92, vs 0.53 in EMEs), we replace current inflation by inflation expectations in the estimated Phillips curves. As shown in Graph 11, the quantile coefficient estimates are highly similar for inflation expectations as those obtained for current inflation, both in advanced economies (second panel) and EMEs (fourth panel). In particular, increases in one-year-ahead inflation expectations move the right-tail of future inflation more to the right, relative to the shift in the left tail.

5.2 Structural factors of inflation risks

As the next set of robustness tests, we examine whether the results are robust to the inclusion of various structural factors that could be relevant for inflation. A large literature has highlighted the implications of trade openness or globalisation (eg Andrews et al (2018); Auer et al (2017); Rogoff (2003)); demographic change (eg Bullard et al (2012); Juselius and Takats (2021)); and market structures, including market power (eg De Loecker et al (2020); Kouvavas et al (2021)). We include the various structural factors in the baseline model, one by one. In particular, for *trade openness*, we include the sum of total exports and imports to GDP; for *financial openness*, we use the sum of external financial assets and liabilities from Lane and Milesi-Ferretti (2018)[17]; and for *demographic change*, we include the young and old-age dependency ratios. Finally, for *market power*, we construct country-level measures of markups using firm-level data from the Worldscope database, using firm-level sales to compute weighted averages for each country. Our measures that show rising markups over time are consistent with those reported in De Loecker et al (2020).

[17] See also https://www.brookings.edu/research/the-external-wealth-of-nations-database/

Our analysis confirms that the baseline results largely hold with the inclusion of such slow-moving factors, in particular the findings about the relevance and nonlinearities associated with inflation targeting for EME inflation (Annex Tables A16-A23).[18] Moreover, our results regarding the structural factors are mostly consistent with previous literature, although in most cases they are not statistically significant. In particular, Annex Tables A16 and A17 show that trade openness is negatively associated with inflation, consistent with Romer (1993) and Lane (1997), with a statistically significant effect in advanced economies.[19] A negative correlation is also obtained for financial openness, similarly to Sen Gupta (2008), even if the coefficients on this variable are not statistically significant (Annex Tables A18 and A19). As to the demographic variables, we find a positive relationship between young-age dependency ratio and future inflation, in line with Juselius and Takats (2021), as well as a negative one between old-age dependence ratio and future inflation (Annex Tables A20 and A21). The latter finding is significant for most quantiles for EMEs and, interestingly, the effect on inflation is larger in the higher quantiles. The negative relationship between the old-age dependency ratio and inflation differs somewhat from the empirical results reported in Juselius and Takats (2021) but is consistent with the model by Bullard et al (2012). Finally, markups have a negative and highly statistically significant relationship with future inflation for most quantiles in advanced economies, with a larger effect on the left tail of the distribution (Annex Table A22).[20] In EMEs, the negative relationship is not statistically significant for any quantile (Annex Table A23).

5.3 Considering other dependent variables

We then estimate the model using alternative dependent variables. Gilchrist and Zakrajsek (2020) consider Phillips curves where inflation based on the *producer price index* (PPI) is the dependent variable, while Forbes (2019) documents that the role of a common, global,

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[18] In the case of advanced economies, the ZLB is no longer statistically significant when the two dependency ratios are included in the model. For EMEs, the non-IT dummy is still statistically significant for most quantiles when the two dependency ratios are included. However, in this case, the relationship between the dummy variable and the future inflation distribution is broadly linear.

[19] Similarly, Andrews et al (2018) find a negative relationship between global value chain participation and PPI inflation.

[20] The negative relationship bears some similarity to the result in Kouvavas et al (2021), where inflation in high markup sectors is found to be less volatile than in low markup sectors in the euro area.

component has been particularly large in the case of PPI inflation. As Annex Tables A24 and A25 show, the coefficients on current inflation are lower across the quantiles when PPI inflation is used in the model. This result is similar to that reported for average inflation in Gilchrist and Zakrajsek (2020). However, we find that the non-linearities across the quantiles are similar as with CPI inflation (with larger coefficients on current inflation in the higher quantiles). For AEs, the effects of the ZLB on the future inflation distribution are now stronger. Moreover, the change in the oil price obtains somewhat larger coefficients in both AEs and EMEs when PPI inflation is used, with slightly more non-linear effects (larger effects in the higher quantiles).

As an alternative dependent variable, we replace four-quarter-ahead inflation by *eight-quarter-ahead inflation*. This results in similar non-linearities as the baseline estimates, for most variables (Annex Tables A26 and A27). However, the coefficient on the oil price switches sign for most of the quantiles. In EMEs, the coefficient on the exchange rate also becomes mostly statistically insignificant, even if the economic impact of exchange rate changes is still larger at the higher quantiles.

5.4 Structural breaks and sub-sample estimates

As a final robustness test, we consider sub-sample estimates. The first two decades of the 2000s were characterised by low inflation and concerns about a flattening Phillips curve, with central banks in many advanced economies and EMEs missing their inflation targets on the downside, especially after the GFC. Moreover, the period before the 2000s featured more frequent financial crises in EMEs. To determine possible structural breaks, we use the test for panels by Ditzen et al (2021), which is based on an F-test and a null hypothesis of no break points. Based on the test results, we choose to run sub-sample estimates for AEs for the post-2003 and for EMEs for the post-1998 periods.[21] Annex Tables A28 and A29 in the Appendix show the estimates for advanced economies and EMEs, respectively.

In advanced economies, the non-linearity related to current inflation in the sub-sample is similar to the longer sample but with lower coefficient estimates across the quantiles (Annex

[21] Specifically, for AEs, the test suggests possible structural breaks in the Phillips curve for 2003 and 2007; for EMEs in 1998, 2002 and 2008. We do not estimate the model solely for the 2009–19 period as it would result in a very short sample. Dummy variables are not considered for these tests and models. See also Altansukh et al (2017) who test for structural breaks in the correlation between domestic and foreign inflation.

Table A28). The sub-sample estimates feature a change in the non-linearity associated with real GDP growth. The coefficient on output growth is now slightly higher at the higher quantiles; yet, output growth matters for inflation at all quantiles. This suggests that the findings related to the non-linearities between economic activity and inflation should be treated with some caution. In EMEs, the sub-sample results differ less from the full sample estimates, with similar non-linearities associated with output growth, inflation and the exchange rate (Annex Table A29).

6. Extensions

Next, we pursue various extensions to the baseline model. We distinguish between commodity importers and exporters and examine the importance of the exchange rate regime. Then, at somewhat greater length, we evaluate the effect of including a measure of financial conditions in the system; compare the model predictions with those from inflation options data; and finally, use our model to study the implications of the first phase of the Covid-19 pandemic shock for inflation risks.

6.1 Commodity importers vs exporters

Given that oil price changes could have different effects on future inflation in commodity importers and exporters, we differentiate between these two groups in the analysis. Specifically, we interact the variable for the oil price change with dummy variables for commodity importers and exporters, respectively, and include both interaction variables simultaneously in the estimated model.[22]

The analysis unveils some differences in the relationship between the oil price change and the future inflation distribution for commodity importers and exporters, especially for EMEs. For EME commodity importers, oil price increases are associated with higher future inflation, but for commodity exporters the magnitude of the relationship is close to zero in

[22] The classification of economies is based on BIS (2019), where commodity exporters are defined as countries where the average share of commodities in export revenues in 2005–14 exceeded 40%.

economic terms and not statistically significant (Annex Table A31).[23] By contrast, for advanced economies, oil price increases are associated with higher inflation for both commodity exporters and importers (Annex Table A30).

6.2 Importance of exchange rate regime

The previous analysis has established the importance of the monetary policy regime, in particular the inflation targeting framework, for inflation risks. However, considering the exchange rate regime separately in the analysis could potentially provide additional insights. To examine this issue, we use the exchange rate classifications in Ilzetzki et al (2019, 2021) and include a dummy variable for exchange rate pegs, as well as an interaction variable between the change in the exchange rate and the peg dummy.[24]

The results confirm that the exchange rate regime matters for inflation risks, even when a potential inflation targeting regime is controlled for. For both advanced economies and EMEs, the existence of a peg is associated with lower future inflation, with a stronger relationship in emerging market economies (Annex Tables A32 and A33). The coefficient on the peg dummy is statistically significant for all other quantiles except the 5th. Interestingly, the size of the coefficient is similar to that of the non-IT dummy in EMEs, with similar non-linearities (larger effect on the right tail of the inflation forecast distribution). By contrast, the interaction variable between the peg dummy and the change in the exchange rate is not statistically significant at any quantile for advanced economies or EMEs.

6.3 Inclusion of financial conditions

As another extension to the baseline specification, we include a measure of financial conditions in the estimated Phillips curves. Lopez-Salido and Loria (2022) find that tighter financial

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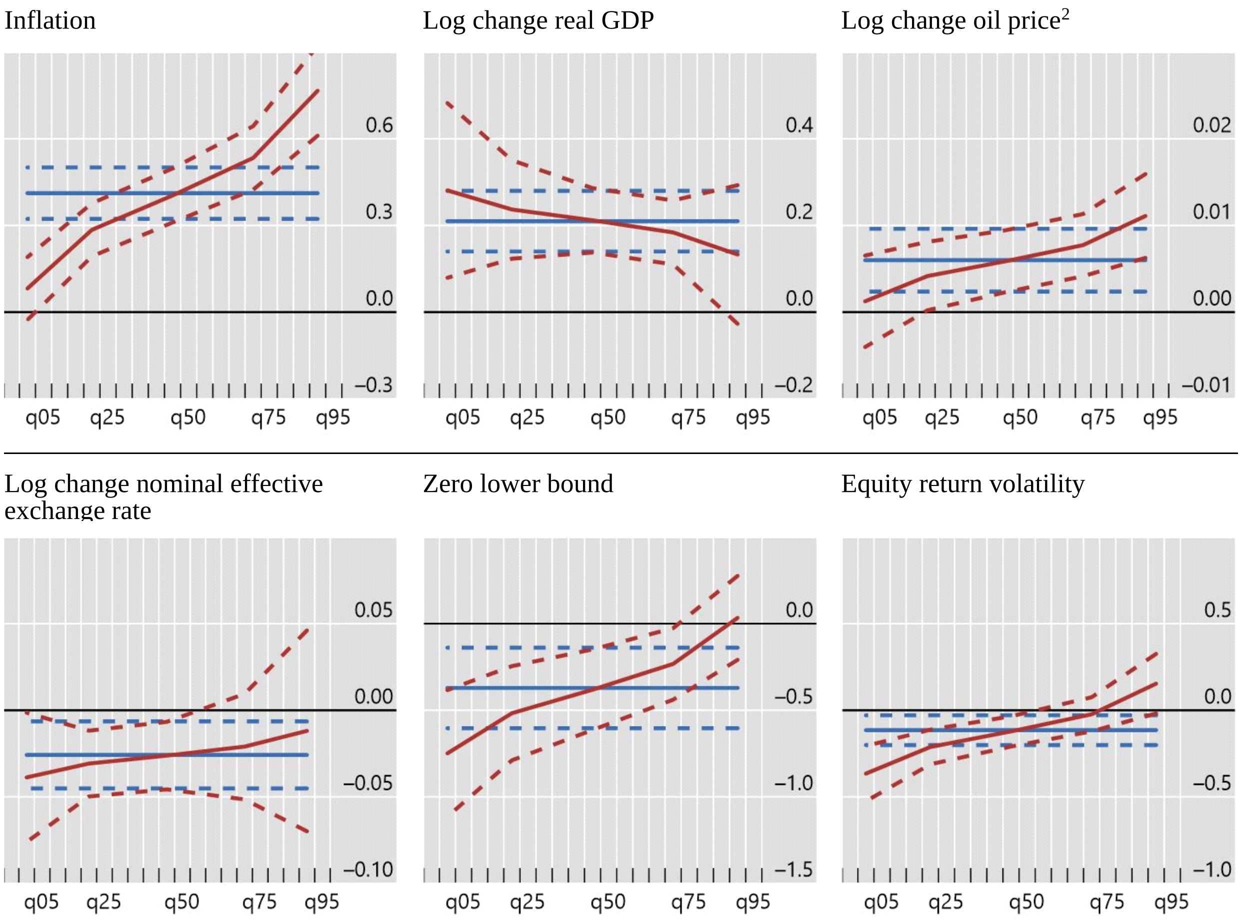
23 Somewhat similarly, Alekhina and Yoshino (2019), using VAR models, find a negative effect of an oil price shock on inflation in an energy exporting country. This result stems from an exchange rate appreciation that reduces imported inflation in an economy where a large share of consumption goods is imported.

24 Specifically, in order to construct the dummy variable, we use the category "1" of the coarse classification that includes, in addition to de facto pegs, the cases of no separate legal tender, a pre-announced peg or a currency board arrangement, and a pre-announced horizontal band that is narrower than or equal to +/- 2%.

conditions are important drivers of downside inflation risks, consistent with their importance in driving left-tail GDP growth outcomes in Adrian et al (2019).

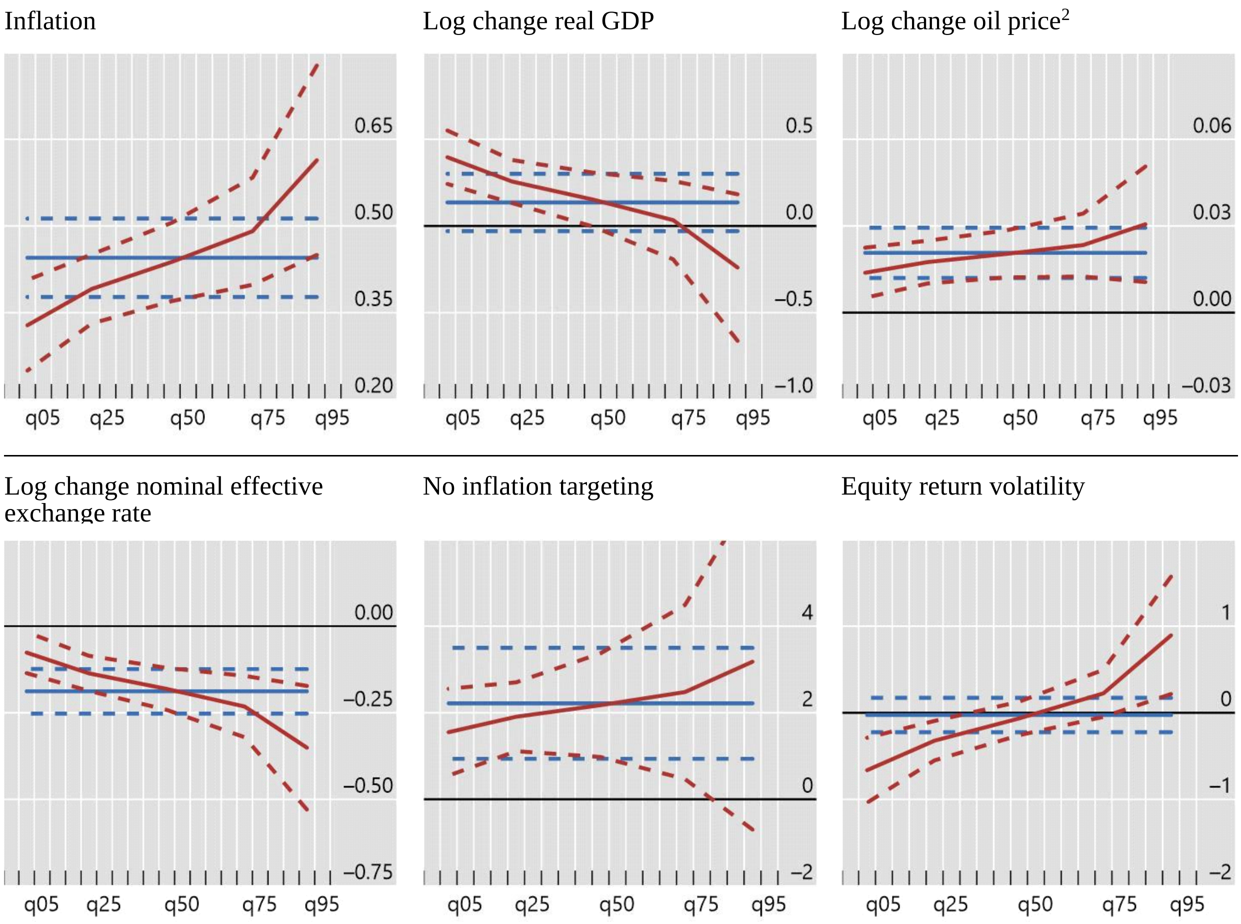


[1] Estimated coefficients from regressing four-quarter-ahead year-on-year CPI inflation on current inflation, log change in real GDP, log change in the oil price, log change in the nominal effective exchange rate, financial conditions and a zero lower bound dummy. OLS regressions in blue and quantile regressions in red; 90% confidence intervals. [2] In domestic currency.

Graph 12: Estimated quantile regression and OLS coefficients, including financial conditions, advanced economies

As a measure of financial conditions, we use the realised volatility in equity returns, measured by the quarterly standard deviation of daily equity returns, based on benchmark indices for the respective economies (eg, S&P500 for the United States). This measure of financial conditions has the benefit of being available for the entire sample of countries. Moreover, Adrian et al (2019) show that their conditional quantile estimates of GDP growth risks appear most sensitive to realised equity volatility, among the variables that constitute the overall financial conditions index. Graphs 12 and 13 show the resulting quantile and least squares Phillips curve estimates for advanced economies and EMEs, respectively.

Our estimates with financial conditions reveal an interesting nonlinearity in that tighter financial conditions widen the entire inflation forecast distribution – both the left and right tail move outward. Regarding the left tail, greater financial volatility and tighter financial conditions could be associated with lower demand and hence lower future growth, which may dampen inflation risks (eg Bloom (2009)). As to the right tail, the importance of financial conditions is consistent with recent work suggesting that firms' pricing behaviour may be affected by the availability of credit, with liquidity constrained firms increasing prices in response to financial shocks in order to avoid accessing external finance (Gilchrist et al (2017)). Our result is also consistent with cost-push shocks – stemming from tighter financial conditions – raising upside inflation risks (eg de Fiore and Tristani (2012)). That said, the effect of tighter financial conditions on right-tail inflation risks is not statistically significant for advanced economies.



[1] Estimated coefficients from regressing four-quarter-ahead year-on-year CPI inflation on current inflation, log change in real GDP, log change in the oil price, log change in the nominal effective exchange rate, financial conditions and a dummy variable for country-years when the central bank did not have an inflation target. OLS regressions in blue and quantile regressions in red; 90% confidence intervals. [2] In domestic currency.

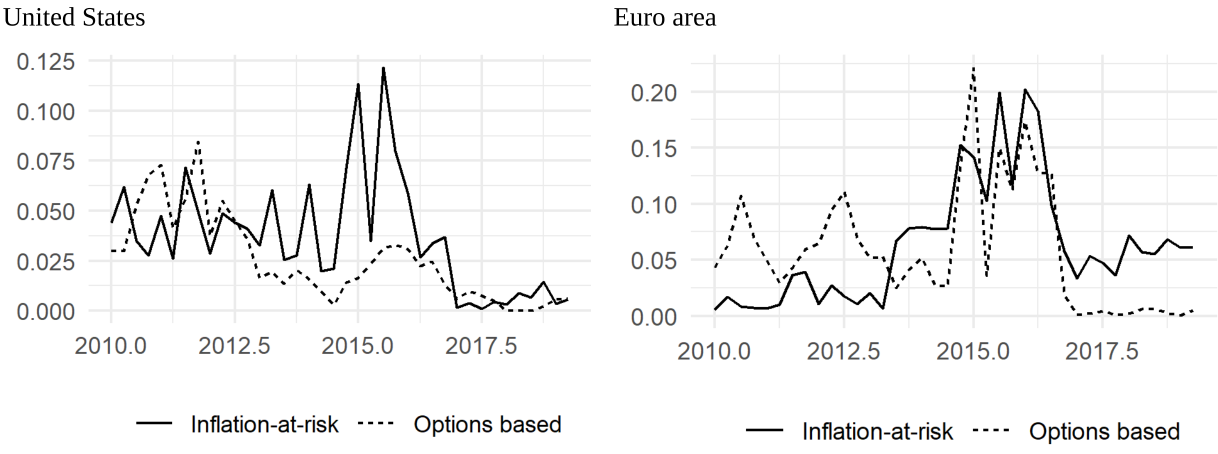
Graph 13: Estimated quantile regression and OLS coefficients, including financial conditions, EMEs

By contrast, tighter financial conditions significantly increase both down and upside inflation risks in EMEs even though the linear least squares estimate is close to zero (Graph 13). Yet, the coefficient estimates for the tails are much higher in magnitude in EMEs than in advanced economies, suggesting that financial conditions are especially important in driving inflation tail outcomes in these countries. The large effect on upside risk in EMEs is consistent with the evidence in Banerjee et al (2020) who show that firms in many EMEs tend to have weaker net liquid asset positions than AE firms, which could lead them to increase prices when faced with tighter financial conditions. They are also in line with tighter financial conditions raising the likelihood of EME currency depreciations (eg Della Corte et al (2018); Ferrari (2019)). Indeed, a quantile regression shows that higher equity volatility is associated with a larger depreciation in the nominal effective exchange rate of the EME currency in the following quarter.[25] Finally, the other coefficient estimates, including the relevance of the ZLB, are broadly unchanged by the inclusion of financial conditions in the estimated Phillips curves.

6.4 Comparing model predictions with inflation options data

In order to compare our inflation-at-risk model's predictions with an alternative methodology, we evaluate deflation probabilities yielded by the model against those from options prices. Cumulative inflation densities derived from traded caps and floors strikes are computed with the methodology of Kitsul and Wright (2013) and Ait-Sahalia and Duarte (2003). A skewed Student-*t* is fitted to these cumulative densities in order to obtain probabilities at non-traded strikes (similarly to Aramonte et al (2019)). We conduct this comparison for the United States and the euro area from 2010 onwards. Note that as our inflation-at-risk model generates country-level distributions, we compute our euro area estimates using the average for Germany, France and Italy for inputs in the model. Equity return volatility is included in the inflation risk model considered here.

[25] The coefficient on equity return volatility is –0.58 on the 50% quantile, –1.55 on the 75% quantile and –3.87 on the 95% quantile, with all coefficients statistically significant at the 5% level.



Graph 14: Estimated deflation probabilities from quantile regression-based inflation risk model and options data

The two methodologies deliver similar outcomes (Graph 14). The broad trends are comparable, with deflation risks rising both in the Phillips curve and the option price-based models during the period of very low inflation in 2015-16. Notably, the inflation risk model delivers a somewhat more timely warning about the looming low inflation, and in the United States the option price-based probability remains contained during 2015-16.

Moreover, the levels of deflation probabilities are highly comparable across the two different models, both for the United States and the euro area. This can be seen as validating the information provided by the inflation-at-risk model. In the euro area, both the Phillips curve and the option price-based model yield deflation probabilities of around 15-20% during 2015-16. Towards the end of the sample, the deflation probability is close to zero in the United States (from both models), while in the euro area, the inflation-at-risk model hints at some lingering deflation concerns that are not evident in options prices.

But perhaps a more important result is one we derive from the difference between the deflation probability from our inflation-at-risk model and that derived from options prices. In particular, the deflation risk premium can be calculated as the difference between the options-implied risk-neutral probability and the estimated “true” probability derived from the inflation-at-risk model. We show that the deflation risk premium is important in driving the negative bond-equity correlation documented by Campbell et al (2020). Indeed, Table 2 shows that the deflation risk premium is positively associated with bond returns (Column (1)), and remains so after controlling either for inflation outcomes or the deflation probability yielded by our model.

Moreover, the deflation risk premium is negatively associated with excess equity returns. The importance of the deflation risk premia – as opposed to deflation risk *per se* – is consistent with Campbell et al (2020) who show that time-varying risk aversion is an important factor that amplifies the negative co-movement between bonds and stocks returns and is needed to quantitatively match the data. Taken together, these findings suggest that the inflation-at-risk model yields a reasonable estimate of the deflation risk premium.

	Dependent variable:					
	Lagged bond return			Lagged equity market return less risk-free rate		
Deflation risk premium	17.698***	22.526***	26.769***	-4.476***	-5.992***	-11.474***
	(1.178)	(2.696)	(5.954)	(0.698)	(0.247)	(0.636)
Inflation		-0.564***			0.177***	
		(0.181)			(0.032)	
Deflation risk from I-at-R model			17.069			-13.168***
			(10.265)			(0.072)
Observations	74	74	74	74	74	74
R-squared	0.046	0.059	0.076	0.017	0.019	0.053

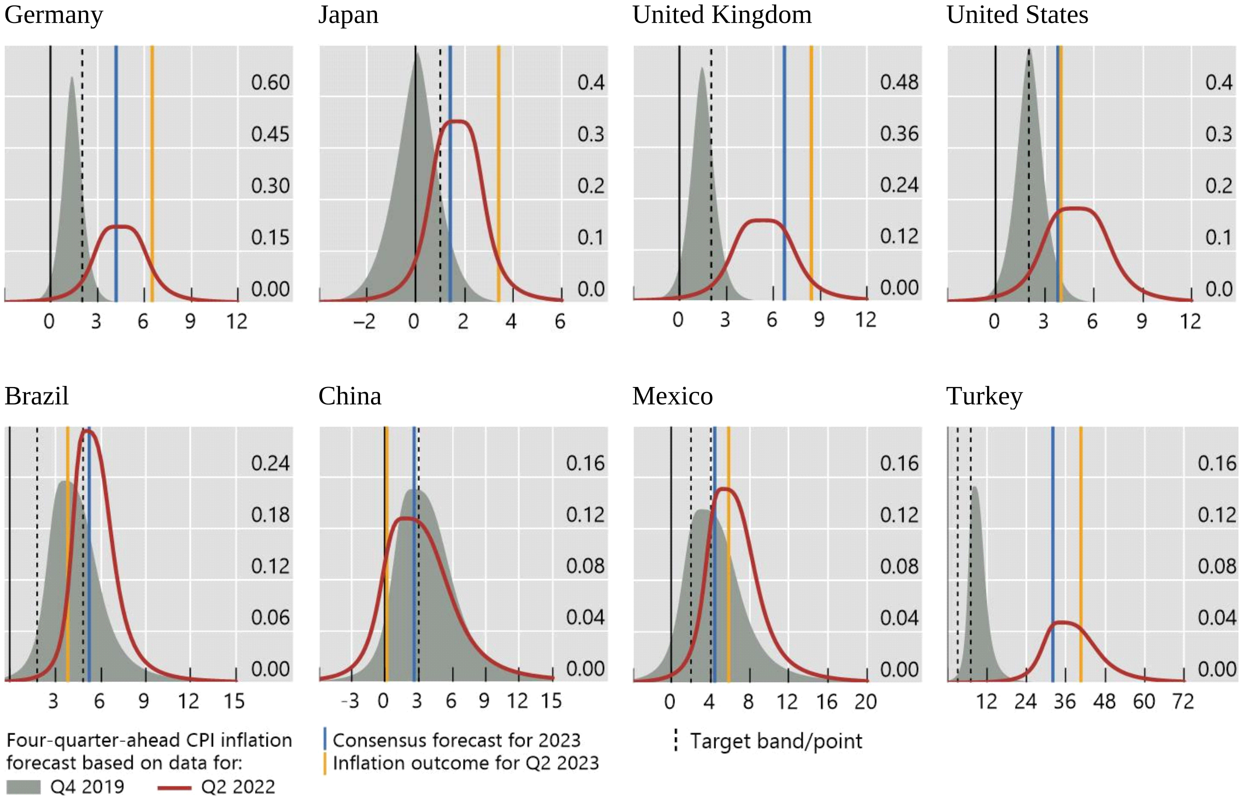
Note: The deflation risk premium is the difference between the probability of deflation obtained from the model based on option prices and that obtained from the inflation-at-risk model. Deflation risk from I-at-R model refers to the probability derived from the inflation-at-risk model. Regressions comprise the United States and the euro area for the period Q1:2010-Q2:2019 and include country fixed effects. Standard errors are clustered by country. Bond returns for the euro area are based on the German government bond.

Table 2: Deflation risk premia and the bond-equity return correlation

6.5 Post-Covid inflation surge

To illustrate the applicability of our empirical approach, we analyse inflation risks during the recovery from the Covid-19 pandemic through the lens of our model. Applying the model to this period is particularly relevant, given that the inflation surge surprised most observers, coming after a long period of persistently low inflation.

Graph 15 shows the conditional inflation forecast distributions in eight major economies, based on Q2 2022 data (red distribution), and compares them with the pre-pandemic forecast distributions based on Q4 2019 data (grey distribution).



Graph 15: Shift in inflation risks after the Covid-19 pandemic

For almost all economies, the inflation forecast distributions have shifted notably to the right (shift from grey to red lines). That is, the changes in current inflation, real GDP growth, oil prices and exchange rates between Q4 2019 and Q2 2022 have shifted the inflation forecast distributions to the right. In addition, they have widened the distributions in advanced economies. These shifts also imply that there was a high probability that central banks would miss their inflation targets (point targets or target ranges; shown as dashed lines) on the upside four quarters later. Consensus forecasts (blue lines) made at the same time as our inflation risk projections are also close to the modes of the inflation risk distributions.

Even with the rightward shifts of the inflation forecast distributions projected with data from Q2 2022, actual inflation outturns in Q2 2023 have been surprising in number of countries. Even though inflation risks increased significantly in Germany, Japan and the United Kingdom, the actual inflation outcomes in Q2 2023 were still relatively high, appearing in the right tail of their inflation forecast distributions. By contrast, inflation outcomes for the United States, Mexico and Turkey were close to the centre of their inflation forecast distributions. The picture in Brazil and China has been quite different. Actual inflation outcomes have been on the weaker side, falling in the left tail of the inflation forecast distribution.

7. Conclusion

In this paper, we find that the shape of the inflation forecast distribution – and the balance of risks – changes significantly over time in response to economic conditions. Among the factors that drive these changes we highlight the monetary policy regime, the level of inflation, the zero lower bound, financial conditions and, in EMEs, the exchange rate.

Within these relationships, our results identify a number of nuances regarding differences in inflation risks across countries. Both exchange rates and monetary policy frameworks have a much stronger influence on inflation risks in EMEs compared with advanced economies. Tighter financial conditions raise both up and downside inflation risks in EMEs while mostly increasing downside risks in advanced economies. Finally, higher oil prices raise inflation risks in EME commodity importers but not in commodity exporters.

Our findings lend support to a risk management approach to monetary policy, one that puts more weight on upside or downside risks than on the modal forecast. However, an "asymmetric" policy response is not a foregone conclusion. In practice, the extent to which measures of inflation risks are incorporated in actual monetary policy decisions is unclear. The policy response depends on contingent circumstances that might not be well captured by a single empirical model. Furthermore, structural models of inflation dynamics used at central banks are generally linear and hence are not suitable for analysing changes in the risks to the inflation outlook and the optimal response to them. We hope that our paper can stimulate further research on these issues.

References

Adrian, T, N Boyarchenko and D Giannone (2019): "Vulnerable growth", *American Economic Review* 109(4), pp. 1263–89.

Agénor, P-R and L Pereira da Silva (2019): *Integrated inflation targeting - Another perspective from the developing world*. Bank for International Settlements.

Ait-Sahalia, Y and J Duarte (2003): "Nonparametric option pricing under shape restrictions", *Journal of Econometrics* 116(1-2), pp. 9–47.

Alekhina, V and N Yoshino (2018): "Impact of world oil prices on an energy exporting economy including monetary policy", *ADBI Working Papers*, no 828.

Altansukh, G, R Becker, G Bratsiotis and D Osborn (2017): "What is the globalisation of inflation?", *Journal of Economic Dynamics and Control* 74, pp. 1–27.

Alvarez, F, M Beraja, M Gonzalez-Rozada and P Andres Neumeyer (2019): "From hyperinflation to stable prices: Argentina's evidence on menu cost models", *Quarterly Journal of Economics* 134(1), pp. 451–505.

An, L and J Wang (2012): "Exchange rate pass-through: Evidence based on vector autoregression with sign restrictions", *Open Economies Review* 23, pp. 359–80.

Andrade, P, E Ghysels and J Idier (2015): "Tails of inflation forecasts and tales of monetary policy", mimeo.

Andrews, D, P Gal and W Witheridge (2018), "A Genie in a Bottle? Globalisation, Competition and Inflation", *OECD Economics Department Working Papers*, No. 1462.

Aramonte, S, M Jahan-Parvar, S Rosen and J Schindler (2019): "Firm-specific risk-neutral distributions with options and CDS", https://ssrn.com/abstract=2908524.

Auer, R, C Borio, and A Filardo (2017): "The globalisation of inflation: the growing importance of global value chains", *BIS Working Papers* No 602.

Azzalini, A and A Capitanio (2003): "Distributions generated by perturbation of symmetry with emphasis on a multivariate skew t-distribution", *Journal of the Royal Statistical Society, Series B* (Statistical Methodology), 65(2), pp. 367–89.

Ball, L and S Cecchetti (1990): "Inflation and uncertainty at short and long horizons", *Brookings Papers on Economic Activity* 1990(1), pp. 215–54.

Banerjee, R, A Illes, E Kharroubi and J Serena (2020): "Covid-19 and corporate sector liquidity", *BIS Bulletin* no. 10.

Bank for International Settlements (2019): *BIS Annual Economic Report 2019*.

Bernanke, B (2017): "How big a problem is the zero lower bound on interest rates?", Blog post, Brookings Institution, 12 April 2017.

Bloom, N (2009): “The impact of uncertainty shocks”, *Econometrica* 77, pp. 623–685.

Borio, C and A Filardo (2007): “Globalisation and inflation: New cross-country evidence on the global determinants of domestic inflation”, *BIS Working Papers* no 227.

Bullard, J, C Garriga and C Waller (2012): “Demographics, redistribution and optimal inflation”, *Federal Reserve Bank of St. Louis Review*, November/December, pp. 419–40.

Busetti, F, M Caivano and D Delle Monache (2021): “Domestic and global determinants of inflation: evidence from expectile regression”, *Oxford Bulletin of Economics and Statistics* 83(4), pp. 982–1001.

Busetti, F, M Caivano and L Rodano (2015): “On the conditional distribution of euro area inflation forecast”, Temi di Discussione, no 1027, Banca d’Italia.

Calligaris, S, C Criscuolo and L Marcolin (2018): “Mark-ups in the digital era", *OECD Science, Technology and Industry Working Papers* 2018/10.

Campbell, J, C Pflueger and L Viceira (2020): “Macroeconomic drivers of bond and equity risks”, *Journal of Political Economy* 128(8), pp. 3148–3185.

Cecchetti, S G (2008): "Measuring the macroeconomic risks posed by asset price booms," in J Y Campbell (ed.), *Asset Prices and Monetary Policy*, Chicago, IL.: University of Chicago Press, pp. 9–43.

Ciccarelli M and B Mojon (2010): “Global inflation”, *The Review of Economics and Statistics*, 92(3) pp 524-535.

De Fiore, F and O Tristani (2012): “Optimal monetary policy in a model of the credit channel”, *The Economic Journal* 123(September), pp. 906-931.

De Gregorio, J (2019): “Inflation targets in Latin America”, *Peterson Institute for International Economics Working Paper* no 19-19.

Della Corte, P, L Sarno, M Schmeling and C Wagner (2018): “Exchange rates and sovereign risk”, http://dx.doi.org/10.2139/ssrn.2354935

De Loecker, J, J Eeckhout and G Unger (2020): “The rise of market power and the macroeconomic implications”, *The Quarterly Journal of Economics* 135(2), pp. 561–644.

Devereux, M and H Siu (2007): “State dependent pricing and business cycle asymmetries”, *International Economic Review*, 47, pp. 281–310.

Ditzen, J, Y Karavias and J Westerlund (2021): “Testing for multiple structural breaks in panel data”, mimeo.

Dovern, J, U Fritsche and J Slacalek (2012): “Disagreement among forecasters in G7 countries”, *The Review of Economics and Statistics* 94(4), pp. 1081–1096.

Engle, R (1983): “Estimates of the variance of U.S. inflation based upon the ARCH model”, *Journal of Money, Credit and Banking* 15(3), pp. 286–301.

Ferrari, M (2019): “Emerging market currencies: the role of global risk, the US dollar and domestic forces”, *ECB Economic Bulletin*, 3/2019.

Forbes, K (2019): “Inflation dynamics: dead, dormant, or determined abroad?”, *Brookings Papers on Economic Activity*, Fall, pp. 257–338.

Forbes, K, J Gagnon and C Collins (2021): “Low inflation bends the Phillips curve around the world”, *NBER Working Paper* no. 29323.

Forbes, K, I Hjortsoe and T Nenova (2018): “The shocks matter: improving our estimates of exchange rate pass-through”, *Journal of International Economics* 114, 255-75.

Furceri, D, P Loungani, J Simon and S Wachter (2016): “Global food prices and domestic inflation: some cross-country evidence”, *Oxford Economic Papers* 68(3), pp. 665-87.

Ghysels, E, L Iania, and J Striaukas (2018): “Quantile-based inflation risk models”, *Working Paper Research* no. 349, National Bank of Belgium.

Gilchrist, S, R Schoenle, J Sim and E Zakrajsek (2017): “Inflation dynamics during the financial crisis”, *American Economic Review* 107(3), pp. 785–823.

Gilchrist, S and E Zakrajsek (2020): “Trade exposure and the evolution of inflation dynamics”, in: G Castex, J Gali and D Saravia (eds), *Changing inflation dynamics, evolving monetary policy*, Central Bank of Chile.

Gopinath, G, E Boz, C Casas, F Diez, P-O Gourinchas and Mikkel Plagborg-Møller (2020): “Dominant currency paradigm”, *American Economic Review* 110(3), pp. 677–719.

Greenspan, A (2004): “Risk and uncertainty in monetary policy”, Remarks at the meetings of the American Economic Association, San Diego, 3 January.

Grier, K and M Perry (1998): “On inflation and inflation uncertainty in the G7 countries”, *Journal of International Money and Finance* 17, pp. 671–89.

Gross, M and W Semmler (2019): “Mind the output gap: the disconnect of growth and inflation during recessions and convex Phillips curves in the euro area”, *Oxford Bulletin of Economics and Statistics* 81(4), pp. 817–48.

Ha, J, A Kose and F Ohnsorge (2021): “One-stop source: a global database of inflation”, *Policy Research Working Paper* no. 9737, World Bank.

Hamilton, J (2018): “Why you should never use the Hodrick-Prescott filter”, *Review of Economics and Statistics* 100(5), pp. 831–43.

Han, H, W Jung and J Lee (2022): “Estimation and inference of quantile impulse response functions by local projections: With applications to VaR dynamics”, *Journal of Financial Econometrics*, nbac026.

Hooper, P, F Mishkin and A Sufi (2020): “Prospects for inflation in a high-pressure economy: is the Phillips curve dead or is it just hibernating?”, *Research in Economics* 74(1), pp. 26–62.

Ilzetzki, E, C Reinhart and K Rogoff (2019): "Exchange arrangements entering the 21st century: which anchor will hold?", *The Quarterly Journal of Economics* 134(2), pp. 599–646.

Ilzetzki, E, C Reinhart and K Rogoff (2021): "Rethinking exchange rate regimes", in: G Gopinath, E Helpman and K Rogoff (eds), *Handbook of International Economics*, vol 5.

Im, K, M Pesaran and Y Shin (2003): "Testing for unit roots in heterogeneous panels", *Journal of Econometrics* 115, pp. 53–74.

Jasova, M, R Moessner and E Takats (2019): "Exchange rate pass-through: What has changed since the crisis?", *International Journal of Central Banking* 15(3), pp. 27–58.

Juselius, M and E Takáts (2021): "Inflation and demography through time", *Journal of Economic Dynamics and Control* 128.

Kilian, L and S Manganelli (2007): "Quantifying the risk of deflation", *Journal of Money, Credit and Banking*, *39*(2-3), pp. 561–590.

Kilian, L and S Manganelli (2008): "The central banker as a risk manager: Estimating the Federal Reserve's preferences under Greenspan", *Journal of Money, Credit and Banking*, *40*(6), pp. 1103–1129.

Kitsul, Y and J Wright (2013): "The economics of options-implied inflation probability density functions", *Journal of Financial Economics* 110(3), pp. 696–711.

Korobilis, D, B Landau, A Musso and A Phella (2021): "The time-varying evolution of inflation risks", *Working Paper Series,* no 2600, European Central Bank.

Kouvavas, O, C Osbat, T Reinelt and I Vansteenkiste (2021): "Markups and inflation cyclicality in the euro area", *ECB Working Papers* no. 2617.

Lane, P (1997): "Inflation in open economies", *Journal of International Economics* 41(3–4), pp. 327–47.

Lane, P and G Milesi-Ferretti (2018): "The external wealth of nations revisited: International financial integration in the aftermath of the Global Financial Crisis", *IMF Economic Review* 66, pp. 189-222.

Lopez-Salido, J and F Loria (2022): "Inflation at risk", Mimeo available at https://dx.doi.org/10.2139/ssrn.4002673.

Machado, J and J Santos Silva (2019): "Quantiles via moments", *Journal of Econometrics* 213(1), pp. 145–173.

Mehrotra, A and J Yetman (2018): "Decaying expectations: what inflation forecasts tell us about the anchoring of inflation expectations", *International Journal of Central Banking* 14(5), pp. 55–101.

Mertens, T and J Williams (2021): "What to expect from the lower bound on interest rates: evidence from derivatives prices", *American Economic Review* 111(8), pp. 2473–2505.

Mishkin, F (2005): “The inflation targeting debate”, John Kuszczak memorial lecture at the Bank of Canada’s annual conference “Issues in inflation targeting”, Ottawa, 28-29 April 2005.

Nakamura, E and J Steinsson (2011): “Price setting in forward-looking customer markets”, *Journal of Monetary Economics* 58, pp. 220–233.

Osorio, C and D Unsal (2013): “Inflation dynamics in Asia: causes, changes, and spillovers from China”, *Journal of Asian Economics* 24 (February), pp. 26–40.

Razi, A and P Loke (2017): “Fan chart: the art and science of communicating uncertainty”, *IFC Bulletin Chapters*, In: Bank for International Settlements (ed.), Statistical implications of the new financial landscape, Vol.43, Bank for International Settlements.

Rogoff, K (2003): “Globalization and global disinflation”, Paper presented at the Federal Reserve Bank of Kansas 2003 Jackson Hole Conference.

Romer, D (1993): “Openness and inflation: Theory and evidence”, *The Quarterly Journal of Economics* 108(4), pp. 869–903.

Rossi, B and T Sekhposyan (2019): ”Alternative tests for correct specification of conditional predictive densities”, *Journal of Econometrics* 208(2), pp. 638–57.

Sen Gupta, A (2008): “Does capital account openness lower inflation?”, *International Economic Journal* 22(4), pp. 471–87.

Siklos, P (2013): "Sources of disagreement in inflation forecasts: An international empirical investigation", *Journal of International Economics* 90(1), pp. 218–31.

Tagliabracci, A (2020): “Asymmetry in the conditional distribution of euro-area inflation”, Temi di Discussione, no 1270, Banca d’Italia.

Taylor, J (2000): “Low inflation, pass-through, and the pricing power of firms”, *European Economic Review* 44(7), pp. 1389–1408.

Williams, J (2014): “Monetary policy at the zero lower bound: putting theory into practice”, *Working Paper, Hutchins Center on Fiscal & Monetary Policy at Brookings*.

Wong, B (2015): “Do inflation expectation propagate the inflationary impact of real oil price shocks?: Evidence from the Michigan Survey”, *Journal of Money Credit and Banking*, 47(8), pp. 1673-1689.

White, H, T Kim and S Manganelli (2015): “VAR for VaR: Measuring tail dependence using multivariate regression quantiles”, *Journal of Econometrics* 187(1) pp. 169-188.

Appendix

- Sources and descriptive statistics: Table A1 and A2
- Baseline regression: Tables A3 and A4
- Full model: Tables A5 and A6
- Robustness tests: Other cyclical drivers of inflation:
  - Table A7: unemployment rate
  - Table A8 and A9: global growth
  - Table A10 and A11: alternative oil prices
  - Table A12 and A13: global food price inflation
  - Table A14 and A15: bilateral US dollar exchange rate
- Robustness tests: Structural factors of inflation risks
  - Table A16 and A17: Trade openness
  - Table A18 and A19: Financial openness
  - Table A20 and A21: Demographics
  - Table A22 and A23: Markups
- Robustness tests: Other dependent variables
  - Tables A24 and A25: Producer price index inflation
  - Tables A26 and A27: Eight-quarter ahead inflation
- Robustness tests: Structural breaks and sub-sample estimates
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- Extensions:
  - Tables A30 and A31 : Commodity importers vs exporters
  - Tables A32 and A33: Exchange rate regime
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  - A1 and A2: Quantile conditional distributions, four-quarter-ahead inflation
  - A3 and A4: Inflation risks: expected shortfall and longrise

Series	Source
Real GDP	National data; Datastream; Oxford Economics
Headline inflation	National data
Producer price inflation	Ha et al (2021)
Nominal effective exchange rate	BIS; JPMorgan
Oil price, WTI	Bloomberg; transformed into local currency using bilateral USD exchange rate from national sources and Datastream
Oil price, Brent	Refinitiv Datastream; transformed into local currency using bilateral USD exchange rate from national sources and Datastream
Food price	World Bank Commodity Price Data; transformed into local currency using bilateral USD exchange rate from national sources and Datastream
Inflation expectations	Consensus Economics
Policy interest rate	National data; Datastream
Unemployment rate	National data; FRED database
Bond returns	Benchmark 10-year Datastream Government index
Excess equity market return	Fama-French factor, downloaded from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
Equity return volatility	Bloomberg; quarterly standard deviation computed from daily return data, using benchmark indices for various economies in local currency
Dependency ratios	World Bank
Trade openness (Imports + exports/GDP)	World Bank
Financial openness (External financial assets + liabilities/GDP)	Lane and Milesi-Ferretti (2018); https://www.brookings.edu/research/the-external-wealth-of-nations-database/
Markups	Worldscope, firm-level data aggregated to country averages, weighted by firm-level sales

Table A1: Data sources

Quantile	AEs	EMEs
5 percent	–0.30	–0.39
25 percent	0.92	1.94
50 percent	1.79	3.96
75 percent	2.59	7.55
95 percent	4.49	20.46

Table A2: Levels of headline inflation at different quantiles, in per cent

	Quantile				
Variables	(0.05)	(0.25)	(0.5)	(0.75)	(0.95)
Inflation	0.194**	0.377***	0.473***	0.580***	0.771***
	(0.0966)	(0.0697)	(0.0606)	(0.0561)	(0.0811)
Change in log real GDP	0.418***	0.312***	0.256***	0.193***	0.0824
	(0.130)	(0.0721)	(0.0472)	(0.0457)	(0.0949)
Change in log neer	-0.0395	-0.0349**	-0.0325**	-0.0298*	-0.0250
	(0.0243)	(0.0148)	(0.0132)	(0.0172)	(0.0289)
Change in log oil price	0.00628**	0.00662***	0.00680***	0.00700***	0.00735***
	(0.00256)	(0.00188)	(0.00177)	(0.00196)	(0.00285)
Observations	1,363	1,363	1,363	1,363	1,363

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A3: Quantile regression estimates, advanced economies

	Quantile				
Variables	(0.05)	(0.25)	(0.5)	(0.75)	(0.95)
Inflation	0.350***	0.455***	0.534***	0.628***	0.820***
	(0.0494)	(0.0453)	(0.0437)	(0.0511)	(0.0673)
Change in log real GDP	0.436***	0.297***	0.192**	0.0674	-0.188
	(0.0986)	(0.0721)	(0.0881)	(0.128)	(0.264)
Change in log neer	-0.0614	-0.134***	-0.189***	-0.253***	-0.386***
	(0.0384)	(0.0307)	(0.0362)	(0.0586)	(0.117)
Change in log oil price	0.0229***	0.0223***	0.0220***	0.0215***	0.0206*
	(0.00582)	(0.00470)	(0.00510)	(0.00638)	(0.0106)
Observations	3,075	3,075	3,075	3,075	3,075

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4: Quantile regression estimates, EMEs

			Quantile		
Variables	(0.05)	(0.25)	(0.5)	(0.75)	(0.95)
Inflation	0.136*	0.322***	0.442***	0.563***	0.785***
	(0.0732)	(0.0581)	(0.0539)	(0.0584)	(0.0849)
Change in log real GDP	0.386***	0.301***	0.247***	0.192***	0.0914
	(0.130)	(0.0748)	(0.0469)	(0.0451)	(0.0965)
Change in log neer	-0.0365*	-0.0336**	-0.0317**	-0.0299	-0.0265
	(0.0220)	(0.0139)	(0.0141)	(0.0183)	(0.0322)
Change in log oil price	0.00571**	0.00635***	0.00677***	0.00718***	0.00795***
	(0.00270)	(0.00192)	(0.00185)	(0.00201)	(0.00293)
ZLB	-0.664***	-0.463***	-0.333***	-0.203*	0.0368
	(0.201)	(0.148)	(0.122)	(0.105)	(0.131)
Observations	1,363	1,363	1,363	1,363	1,363

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A5: Quantile regression estimates, full model, advanced economies

			Quantile		
Variables	(0.05)	(0.25)	(0.5)	(0.75)	(0.95)
Inflation	0.321***	0.415***	0.486***	0.572***	0.747***
	(0.0481)	(0.0411)	(0.0410)	(0.0488)	(0.0790)
Change in log real GDP	0.414***	0.281***	0.182**	0.0612	-0.186
	(0.0949)	(0.0695)	(0.0845)	(0.138)	(0.264)
Change in log neer	-0.0711*	-0.138***	-0.187***	-0.247***	-0.370***
	(0.0377)	(0.0312)	(0.0377)	(0.0533)	(0.106)
Change in log oil price	0.0214***	0.0215***	0.0215***	0.0216***	0.0217*
	(0.00585)	(0.00473)	(0.00515)	(0.00643)	(0.0115)
Not inflation targeter	1.658***	1.981***	2.220***	2.512**	3.110*
	(0.585)	(0.498)	(0.632)	(0.988)	(1.851)
Observations	3,075	3,075	3,075	3,075	3,075

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A6: Quantile regression estimates, full model, EMEs

			Quantile		
Variables	(0.05)	(0.25)	(0.5)	(0.75)	(0.95)
Inflation	0.0685	0.267***	0.398***	0.531***	0.790***
	(0.0627)	(0.0614)	(0.0592)	(0.0622)	(0.0834)
Unemployment rate	-0.0628**	-0.0726***	-0.0790***	-0.0856**	-0.0983
	(0.0312)	(0.0242)	(0.0271)	(0.0364)	(0.0612)
Change in log neer	-0.0352**	-0.0338***	-0.0328**	-0.0319	-0.0301
	(0.0174)	(0.0131)	(0.0155)	(0.0198)	(0.0331)
Change in log oil price	0.0106***	0.00962***	0.00899***	0.00835***	0.00711**
	(0.00208)	(0.00164)	(0.00171)	(0.00197)	(0.00296)
ZLB	-0.628***	-0.432***	-0.303***	-0.172*	0.0836
	(0.184)	(0.135)	(0.110)	(0.0994)	(0.138)
Observations	1,357	1,357	1,357	1,357	1,357

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A7: Quantile regression estimates, with unemployment rate, advanced economies

			Quantile		
Variables	(0.05)	(0.25)	(0.5)	(0.75)	(0.95)
Inflation	0.128	0.324***	0.444***	0.561***	0.789***
	(0.0822)	(0.0612)	(0.0561)	(0.0587)	(0.0820)
Change in log real GDP	0.210*	0.160**	0.130**	0.101	0.0438
	(0.122)	(0.0720)	(0.0562)	(0.0729)	(0.126)
Change in log global real GDP	0.564***	0.433***	0.354***	0.276***	0.124
	(0.111)	(0.0718)	(0.0663)	(0.0835)	(0.131)
Change in log neer	-0.0576**	-0.0458***	-0.0386***	-0.0316*	-0.0178
	(0.0266)	(0.0162)	(0.0130)	(0.0182)	(0.0331)
Change in log oil price	-0.000831	0.00182	0.00345*	0.00502**	0.00811***
	(0.00281)	(0.00202)	(0.00184)	(0.00201)	(0.00259)
ZLB	-0.706***	-0.477***	-0.338***	-0.202*	0.0638
	(0.198)	(0.138)	(0.121)	(0.109)	(0.132)
Observations	1,363	1,363	1,363	1,363	1,363

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A8: Quantile regression estimates, model with global growth, advanced economies

Variables	Quantile (0.05)	(0.25)	(0.5)	(0.75)	(0.95)
Inflation	0.331***	0.424***	0.496***	0.579***	0.763***
	(0.0450)	(0.0399)	(0.0395)	(0.0510)	(0.0830)
Change in log real GDP	0.225***	0.136**	0.0677	-0.0120	-0.187
	(0.0774)	(0.0648)	(0.0931)	(0.144)	(0.265)
Change in log global real GDP	1.288***	1.094***	0.944***	0.769***	0.386
	(0.191)	(0.126)	(0.133)	(0.209)	(0.423)
Change in log neer	-0.102***	-0.160***	-0.205***	-0.257***	-0.372***
	(0.0356)	(0.0323)	(0.0374)	(0.0547)	(0.103)
Change in log oil price	8.80e-06	0.00378	0.00671	0.0101	0.0176*
	(0.00570)	(0.00509)	(0.00541)	(0.00682)	(0.0102)
Not inflation targeter	1.526**	1.881***	2.156***	2.475***	3.178*
	(0.608)	(0.502)	(0.630)	(0.945)	(1.748)
Observations	3,072	3,072	3,072	3,072	3,072

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A9: Quantile regression estimates, model with global growth, EMEs

Variables	Quantile (0.05)	(0.25)	(0.5)	(0.75)	(0.95)
Inflation	0.139*	0.321***	0.440***	0.562***	0.781***
	(0.0723)	(0.0582)	(0.0587)	(0.0600)	(0.0815)
Change in log real GDP	0.366***	0.293***	0.245***	0.195***	0.107
	(0.126)	(0.0728)	(0.0484)	(0.0471)	(0.0985)
Change in log neer	-0.0357	-0.0331**	-0.0314**	-0.0297	-0.0265
	(0.0229)	(0.0140)	(0.0133)	(0.0184)	(0.0319)
Change in log oil price	0.00834***	0.00790***	0.00762***	0.00733***	0.00680***
	(0.00261)	(0.00201)	(0.00186)	(0.00190)	(0.00260)
ZLB	-0.661***	-0.464***	-0.336***	-0.204*	0.0332
	(0.197)	(0.146)	(0.118)	(0.105)	(0.132)
Observations	1,363	1,363	1,363	1,363	1,363

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A10: Quantile regression estimates, model with Brent oil price, advanced economies

Variables	(0.05)	(0.25)	Quantile (0.5)	(0.75)	(0.95)
Inflation	0.323***	0.416***	0.487***	0.572***	0.749***
	(0.0484)	(0.0397)	(0.0388)	(0.0508)	(0.0800)
Change in log real GDP	0.405***	0.278***	0.179**	0.0623	-0.182
	(0.0942)	(0.0684)	(0.0879)	(0.131)	(0.276)
Change in log neer	-0.0722**	-0.137***	-0.187***	-0.246***	-0.370***
	(0.0345)	(0.0312)	(0.0363)	(0.0552)	(0.107)
Change in log oil price	0.0239***	0.0230***	0.0223***	0.0216***	0.0199*
	(0.00540)	(0.00434)	(0.00495)	(0.00632)	(0.0107)
Not inflation targeter	1.656***	1.978***	2.226***	2.522***	3.140*
	(0.570)	(0.505)	(0.638)	(0.968)	(1.853)
Observations	3,075	3,075	3,075	3,075	3,075

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A11: Quantile regression estimates, model with Brent oil price, EMEs

Variables	(0.05)	(0.25)	Quantile (0.5)	(0.75)	(0.95)
Inflation	0.135*	0.322***	0.441***	0.562***	0.790***
	(0.0702)	(0.0587)	(0.0559)	(0.0633)	(0.0783)
Change in log real GDP	0.377***	0.296***	0.243***	0.190***	0.0909
	(0.131)	(0.0745)	(0.0477)	(0.0442)	(0.0947)
Change in log neer	-0.0397	-0.0313*	-0.0259**	-0.0205	-0.0103
	(0.0286)	(0.0161)	(0.0126)	(0.0171)	(0.0308)
Change in log oil price	0.00530**	0.00600***	0.00644***	0.00689***	0.00774***
	(0.00268)	(0.00200)	(0.00171)	(0.00201)	(0.00297)
ZLB	-0.660***	-0.458***	-0.329***	-0.198*	0.0479
	(0.201)	(0.147)	(0.117)	(0.104)	(0.132)
Change in log food price	-0.00195	0.00304	0.00623	0.00947	0.0156
	(0.00721)	(0.00488)	(0.00534)	(0.00687)	(0.0109)
Observations	1,363	1,363	1,363	1,363	1,363

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A12: Quantile regression estimates, model with food prices, advanced economies

Variables	Quantile (0.05)	(0.25)	(0.5)	(0.75)	(0.95)
Inflation	0.313***	0.410***	0.483***	0.569***	0.749***
	(0.0469)	(0.0383)	(0.0410)	(0.0498)	(0.0808)
Change in log real GDP	0.414***	0.276***	0.172**	0.0505	-0.205
	(0.0964)	(0.0678)	(0.0873)	(0.136)	(0.264)
Change in log neer	-0.0470	-0.0977***	-0.136***	-0.181***	-0.274***
	(0.0334)	(0.0298)	(0.0389)	(0.0568)	(0.102)
Change in log oil price	0.0131**	0.0141***	0.0149***	0.0158**	0.0176*
	(0.00582)	(0.00481)	(0.00489)	(0.00637)	(0.0106)
Not inflation targeter	1.780***	2.046***	2.246***	2.481**	2.974*
	(0.615)	(0.497)	(0.667)	(0.974)	(1.805)
Change in log food price	0.0480***	0.0623***	0.0732***	0.0858***	0.112***
	(0.0136)	(0.0111)	(0.0130)	(0.0171)	(0.0292)
Observations	3,072	3,072	3,072	3,072	3,072

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A13: Quantile regression estimates, model with food prices, EMEs

Variables	Quantile (0.05)	(0.25)	(0.5)	(0.75)	(0.95)
Inflation	0.139*	0.322***	0.440***	0.562***	0.788***
	(0.0711)	(0.0580)	(0.0602)	(0.0603)	(0.0741)
Change in log real GDP	0.372***	0.294***	0.243***	0.190***	0.0933
	(0.119)	(0.0682)	(0.0474)	(0.0489)	(0.0961)
Change in log USD	-9.80e-05	0.00353	0.00588	0.00829	0.0128
	(0.00583)	(0.00480)	(0.00685)	(0.0106)	(0.0168)
Change in log oil price	0.00605***	0.00678***	0.00725***	0.00774***	0.00864***
	(0.00226)	(0.00172)	(0.00171)	(0.00190)	(0.00297)
ZLB	-0.661***	-0.464***	-0.336***	-0.204*	0.0400
	(0.203)	(0.144)	(0.117)	(0.105)	(0.128)
Observations	1,363	1,363	1,363	1,363	1,363

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A14: Quantile regression estimates with bilateral US dollar exchange rate, advanced economies

Variables	Quantile (0.05)	(0.25)	(0.5)	(0.75)	(0.95)
Inflation	0.326***	0.424***	0.499***	0.592***	0.784***
	(0.0461)	(0.0407)	(0.0421)	(0.0528)	(0.0859)
Change in log real GDP	0.415***	0.284***	0.184**	0.0587	-0.197
	(0.0990)	(0.0761)	(0.0882)	(0.129)	(0.264)
Change in log USD	-0.0427	-0.0897***	-0.126***	-0.171***	-0.264***
	(0.0293)	(0.0277)	(0.0310)	(0.0448)	(0.0905)
Change in log oil price	0.0260***	0.0289***	0.0311***	0.0338***	0.0393***
	(0.00648)	(0.00544)	(0.00531)	(0.00682)	(0.0129)
Not inflation targeter	1.756***	1.922***	2.051***	2.210**	2.537
	(0.592)	(0.495)	(0.667)	(0.955)	(1.894)
Observations	3,083	3,083	3,083	3,083	3,083

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A15: Quantile regression estimates with bilateral US dollar exchange rate, EMEs

Variables	Quantile (0.05)	(0.25)	(0.5)	(0.75)	(0.95)
Inflation	0.121	0.295***	0.410***	0.524***	0.733***
	(0.0748)	(0.0551)	(0.0554)	(0.0600)	(0.0983)
Change in log real GDP	0.329***	0.278***	0.243***	0.210***	0.148**
	(0.0980)	(0.0628)	(0.0445)	(0.0403)	(0.0716)
Change in log neer	-0.0339	-0.0319**	-0.0306**	-0.0294*	-0.0270
	(0.0207)	(0.0140)	(0.0132)	(0.0176)	(0.0298)
Change in log oil price	0.00547**	0.00627***	0.00680***	0.00733***	0.00829***
	(0.00257)	(0.00190)	(0.00170)	(0.00195)	(0.00304)
ZLB	-0.369*	-0.227	-0.132	-0.0386	0.134
	(0.199)	(0.144)	(0.111)	(0.108)	(0.147)
Trade openness	-0.0207*	-0.0193**	-0.0185***	-0.0176**	-0.0160
	(0.0111)	(0.00803)	(0.00704)	(0.00715)	(0.00979)
Observations	1,363	1,363	1,363	1,363	1,363

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A16: Quantile regression estimates, model with trade openness, advanced economies

Variables	(0.05)	(0.25)	Quantile (0.5)	(0.75)	(0.95)
Inflation	0.319***	0.408***	0.476***	0.558***	0.728***
	(0.0478)	(0.0401)	(0.0439)	(0.0523)	(0.0892)
Change in log real GDP	0.421***	0.286***	0.181*	0.0559	-0.203
	(0.0994)	(0.0720)	(0.0925)	(0.140)	(0.288)
Change in log neer	-0.0755**	-0.142***	-0.192***	-0.253***	-0.379***
	(0.0363)	(0.0321)	(0.0390)	(0.0568)	(0.110)
Change in log oil price	0.0221***	0.0222***	0.0223***	0.0223***	0.0225*
	(0.00548)	(0.00451)	(0.00514)	(0.00676)	(0.0119)
Not inflation targeter	1.652***	1.944***	2.168***	2.438**	2.994
	(0.593)	(0.495)	(0.677)	(1.004)	(1.942)
Trade openness	-0.00222	-0.00623	-0.00931	-0.0130	-0.0206
	(0.00942)	(0.00866)	(0.00900)	(0.0101)	(0.0171)
Observations	2,957	2,957	2,957	2,957	2,957

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A17: Quantile regression estimates, model with trade openness, EMEs

Variables	(0.05)	(0.25)	Quantile (0.5)	(0.75)	(0.95)
Inflation	0.0979	0.294***	0.421***	0.553***	0.810***
	(0.0780)	(0.0617)	(0.0577)	(0.0594)	(0.0811)
Change in log real GDP	0.345***	0.273***	0.227***	0.178***	0.0843
	(0.126)	(0.0804)	(0.0502)	(0.0440)	(0.0917)
Change in log neer	-0.0350	-0.0317**	-0.0296**	-0.0274	-0.0230
	(0.0235)	(0.0155)	(0.0146)	(0.0210)	(0.0380)
Change in log oil price	0.00303	0.00558***	0.00723***	0.00894***	0.0123***
	(0.00287)	(0.00207)	(0.00200)	(0.00227)	(0.00352)
ZLB	-0.925***	-0.644***	-0.462***	-0.273	0.0945
	(0.223)	(0.166)	(0.168)	(0.205)	(0.316)
Financial openness	-0.0743	-0.0561	-0.0443	-0.0321	-0.00828
	(0.0672)	(0.0413)	(0.0346)	(0.0293)	(0.0466)
Observations	1,231	1,231	1,231	1,231	1,231

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A18: Quantile regression estimates, model with financial openness, advanced economies

Variables	(0.05)	(0.25)	Quantile (0.5)	(0.75)	(0.95)
Inflation	0.329***	0.408***	0.471***	0.547***	0.699***
	(0.0542)	(0.0448)	(0.0456)	(0.0548)	(0.0866)
Change in log real GDP	0.428***	0.285***	0.173*	0.0376	-0.236
	(0.109)	(0.0743)	(0.0975)	(0.147)	(0.304)
Change in log neer	-0.0711*	-0.133***	-0.182***	-0.241***	-0.361***
	(0.0366)	(0.0325)	(0.0412)	(0.0573)	(0.105)
Change in log oil price	0.0196***	0.0213***	0.0226***	0.0242***	0.0273**
	(0.00557)	(0.00502)	(0.00552)	(0.00722)	(0.0129)
Not inflation targeter	1.779***	2.215***	2.559***	2.976***	3.814**
	(0.643)	(0.562)	(0.659)	(0.990)	(1.781)
Financial openness	-0.0315	-0.0245	-0.0191	-0.0125	0.000876
	(0.395)	(0.347)	(0.306)	(0.250)	(0.304)
Observations	2,748	2,748	2,748	2,748	2,748

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A19: Quantile regression estimates, model with financial openness, EMEs

Variables	(0.05)	(0.25)	Quantile (0.5)	(0.75)	(0.95)
Inflation	0.135**	0.310***	0.423***	0.541***	0.752***
	(0.0658)	(0.0502)	(0.0546)	(0.0651)	(0.102)
Change in log real GDP	0.347***	0.274***	0.227***	0.178***	0.0897
	(0.0954)	(0.0594)	(0.0444)	(0.0464)	(0.0797)
Change in log neer	-0.0375*	-0.0346**	-0.0327***	-0.0307*	-0.0272
	(0.0224)	(0.0137)	(0.0122)	(0.0170)	(0.0308)
Change in log oil price	0.00659***	0.00683***	0.00698***	0.00714***	0.00742**
	(0.00241)	(0.00172)	(0.00170)	(0.00198)	(0.00289)
ZLB	-0.432	-0.262	-0.152	-0.0378	0.167
	(0.291)	(0.210)	(0.170)	(0.157)	(0.199)
Old-age dependency ratio	-0.0232	-0.0257	-0.0273	-0.0289	-0.0319
	(0.0553)	(0.0499)	(0.0462)	(0.0489)	(0.0603)
Young-age dependency ratio	0.0818	0.0579	0.0426	0.0265	-0.00213
	(0.0922)	(0.0569)	(0.0422)	(0.0356)	(0.0627)
Observations	1,363	1,363	1,363	1,363	1,363

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A20: Quantile regression estimates, model with dependency ratios, advanced economies

Variables	Quantile (0.05)	(0.25)	(0.5)	(0.75)	(0.95)
Inflation	0.331***	0.411***	0.472***	0.544***	0.693***
	(0.0494)	(0.0407)	(0.0426)	(0.0518)	(0.0937)
Change in log real GDP	0.425***	0.272***	0.153*	0.0148	-0.274
	(0.103)	(0.0683)	(0.0874)	(0.137)	(0.292)
Change in log neer	-0.0668*	-0.138***	-0.193***	-0.256***	-0.389***
	(0.0366)	(0.0314)	(0.0396)	(0.0578)	(0.112)
Change in log oil price	0.0235***	0.0228***	0.0223***	0.0217***	0.0205*
	(0.00577)	(0.00498)	(0.00498)	(0.00638)	(0.0117)
Not inflation targeter	1.850**	1.795***	1.752***	1.703*	1.599
	(0.759)	(0.531)	(0.611)	(0.902)	(1.809)
Old-age dependency ratio	0.00350	-0.0770	-0.139**	-0.212***	-0.363***
	(0.0796)	(0.0690)	(0.0689)	(0.0805)	(0.115)
Young-age dependency ratio	-0.0251	0.00502	0.0284	0.0555	0.112
	(0.0543)	(0.0378)	(0.0332)	(0.0426)	(0.0855)
Observations	3,075	3,075	3,075	3,075	3,075

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A21: Quantile regression estimates, model with dependency ratios, EMEs

Variables	Quantile (0.05)	(0.25)	(0.5)	(0.75)	(0.95)
Inflation	0.0592	0.257***	0.376***	0.504***	0.742***
	(0.0616)	(0.0449)	(0.0455)	(0.0536)	(0.0923)
Change in log real GDP	0.226***	0.202***	0.188***	0.173***	0.144*
	(0.0866)	(0.0504)	(0.0348)	(0.0389)	(0.0797)
Change in log neer	-0.0379*	-0.0312**	-0.0271*	-0.0228	-0.0146
	(0.0217)	(0.0126)	(0.0140)	(0.0204)	(0.0378)
Change in log oil price	0.00762***	0.00770***	0.00775***	0.00780***	0.00790***
	(0.00251)	(0.00168)	(0.00162)	(0.00190)	(0.00302)
ZLB	-0.490**	-0.366**	-0.291**	-0.212*	-0.0627
	(0.213)	(0.161)	(0.140)	(0.122)	(0.148)
Markup	-9.937***	-6.946***	-5.148***	-3.215***	0.383
	(2.201)	(1.417)	(1.050)	(1.081)	(1.824)
Observations	1,363	1,363	1,363	1,363	1,363

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A22: Quantile regression estimates, model with markups, advanced economies

Variables	(0.05)	(0.25)	Quantile (0.5)	(0.75)	(0.95)
Inflation	0.303***	0.387***	0.447***	0.521***	0.684***
	(0.0499)	(0.0353)	(0.0387)	(0.0564)	(0.0967)
Change in log real GDP	0.535***	0.370***	0.253**	0.107	-0.212
	(0.0808)	(0.0646)	(0.102)	(0.165)	(0.338)
Change in log neer	-0.0689*	-0.134***	-0.181***	-0.238***	-0.365***
	(0.0382)	(0.0311)	(0.0396)	(0.0597)	(0.119)
Change in log oil price	0.0179***	0.0188***	0.0194***	0.0201***	0.0217*
	(0.00463)	(0.00356)	(0.00419)	(0.00604)	(0.0117)
Not inflation targeter	1.368***	1.731***	1.989***	2.311**	3.014
	(0.527)	(0.451)	(0.680)	(1.043)	(1.982)
Markup	-5.622	-5.491	-5.397	-5.281	-5.027
	(3.666)	(3.452)	(3.576)	(3.929)	(5.601)
Observations	2,719	2,719	2,719	2,719	2,719

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A23: Quantile regression estimates, model with markups, EMEs

Variables	(0.05)	(0.25)	Quantile (0.5)	(0.75)	(0.95)
PPI inflation	-0.171*	-0.0903	-0.0419	0.0187	0.0987**
	(0.0996)	(0.0696)	(0.0505)	(0.0387)	(0.0446)
Change in log real GDP	0.819***	0.746***	0.703***	0.648***	0.576***
	(0.209)	(0.154)	(0.130)	(0.148)	(0.208)
Change in log neer	-0.0829	-0.0467	-0.0249	0.00251	0.0386
	(0.0871)	(0.0842)	(0.0841)	(0.0920)	(0.113)
Change in log oil price	0.0341***	0.0443***	0.0504***	0.0581***	0.0682***
	(0.00635)	(0.00478)	(0.00700)	(0.0117)	(0.0191)
ZLB	-1.590***	-1.388***	-1.265***	-1.112**	-0.910
	(0.612)	(0.494)	(0.461)	(0.543)	(0.703)
Observations	1,324	1,324	1,324	1,324	1,324

Note: Dependent variable is four-quarter-ahead PPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A24: Quantile regression estimates, model with PPI inflation, advanced economies

Variables	Quantile (0.05)	(0.25)	(0.5)	(0.75)	(0.95)
PPI inflation	0.0516	0.127**	0.187***	0.258***	0.380***
	(0.0633)	(0.0599)	(0.0636)	(0.0798)	(0.117)
Change in log real GDP	0.506***	0.255***	0.0583	-0.177*	-0.580***
	(0.116)	(0.0936)	(0.0913)	(0.102)	(0.162)
Change in log neer	-0.0651	-0.110**	-0.145**	-0.187*	-0.259*
	(0.0552)	(0.0463)	(0.0636)	(0.0980)	(0.151)
Change in log oil price	0.0553***	0.0601***	0.0638***	0.0682***	0.0758***
	(0.00978)	(0.00788)	(0.00952)	(0.0130)	(0.0215)
Not inflation targeter	3.461***	4.065***	4.540***	5.108***	6.081***
	(0.949)	(0.909)	(1.118)	(1.426)	(2.152)
Observations	2,415	2,415	2,415	2,415	2,415

Note: Dependent variable is four-quarter-ahead PPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A25: Quantile regression estimates, model with PPI inflation, EMEs

Variables	Quantile (0.05)	(0.25)	(0.5)	(0.75)	(0.95)
Inflation	0.169***	0.209***	0.239***	0.268***	0.315***
	(0.0433)	(0.0421)	(0.0479)	(0.0547)	(0.0725)
Change in log real GDP	0.291**	0.225***	0.178***	0.130***	0.0533
	(0.128)	(0.0835)	(0.0597)	(0.0435)	(0.0646)
Change in log neer	-0.0629***	-0.0543***	-0.0480***	-0.0418***	-0.0317
	(0.0214)	(0.0128)	(0.0101)	(0.0114)	(0.0199)
Change in log oil price	-0.0169***	-0.00946***	-0.00404***	0.00136	0.0101***
	(0.00310)	(0.00171)	(0.00123)	(0.00153)	(0.00253)
ZLB	-0.567***	-0.425**	-0.322**	-0.219	-0.0526
	(0.190)	(0.165)	(0.148)	(0.140)	(0.147)
Observations	1,311	1,311	1,311	1,311	1,311

Note: Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A26: Quantile regression estimates, eight-quarter-ahead inflation as dependent variable, advanced economies

Variables	(0.05)	(0.25)	Quantile (0.5)	(0.75)	(0.95)
Inflation	0.179***	0.229***	0.266***	0.314***	0.416***
	(0.0426)	(0.0429)	(0.0605)	(0.0870)	(0.144)
Change in log real GDP	0.116	0.155***	0.184***	0.222***	0.300*
	(0.0730)	(0.0479)	(0.0489)	(0.0827)	(0.173)
Change in log neer	0.0221	-0.0157	-0.0435	-0.0804*	-0.157*
	(0.0388)	(0.0319)	(0.0342)	(0.0448)	(0.0823)
Change in log oil price	-0.00529	-0.00679*	-0.00790	-0.00937	-0.0124
	(0.00505)	(0.00413)	(0.00511)	(0.00768)	(0.0148)
Not inflation targeter	0.789	2.097***	3.060***	4.338***	6.985**
	(0.656)	(0.518)	(0.873)	(1.568)	(3.238)
Observations	2,950	2,950	2,950	2,950	2,950

Note: Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A27: Quantile regression estimates, eight-quarter-ahead inflation as dependent variable, EMEs

Variables	(0.05)	(0.25)	Quantile (0.5)	(0.75)	(0.95)
Inflation	0.0675	0.147**	0.221***	0.236***	0.308***
	(0.0885)	(0.0622)	(0.0574)	(0.0470)	(0.0474)
Change in log real GDP	0.215*	0.254***	0.323***	0.297***	0.332***
	(0.122)	(0.0872)	(0.0577)	(0.0542)	(0.0652)
Change in log neer	-0.0168	-0.0215	-0.0275*	-0.0267	-0.0309
	(0.0264)	(0.0224)	(0.0165)	(0.0268)	(0.0372)
Change in log oil price	0.00939***	0.00840***	0.00671***	0.00729***	0.00640
	(0.00240)	(0.00139)	(0.00160)	(0.00253)	(0.00394)
Observations	739	739	943	739	739

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A28: Quantile regression estimates, post-2003, advanced economies

Variables	(0.05)	(0.25)	Quantile (0.5)	(0.75)	(0.95)
Inflation	0.250***	0.347***	0.416***	0.497***	0.669***
	(0.0532)	(0.0590)	(0.0675)	(0.0791)	(0.115)
Change in log real GDP	0.328***	0.214***	0.133	0.0384	-0.164
	(0.100)	(0.0705)	(0.111)	(0.166)	(0.333)
Change in log neer	-0.104***	-0.139***	-0.163***	-0.192***	-0.253***
	(0.0302)	(0.0326)	(0.0321)	(0.0413)	(0.0600)
Change in log oil price	0.0229***	0.0257***	0.0277***	0.0301***	0.0351***
	(0.00611)	(0.00653)	(0.00571)	(0.00606)	(0.00967)
Observations	2,479	2,479	2,479	2,479	2,479

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A29: Quantile regression estimates, post-1998, EMEs

Variables	(0.05)	(0.25)	Quantile (0.5)	(0.75)	(0.95)
Inflation	0.145**	0.323***	0.442***	0.561***	0.785***
	(0.0694)	(0.0551)	(0.0551)	(0.0577)	(0.0810)
Change in log real GDP	0.383***	0.302***	0.248***	0.193***	0.0907
	(0.118)	(0.0695)	(0.0471)	(0.0464)	(0.0943)
Change in log neer	-0.0403*	-0.0369***	-0.0347***	-0.0324*	-0.0282
	(0.0215)	(0.0129)	(0.0123)	(0.0173)	(0.0321)
Change in log oil pr. (exporter)	0.0147**	0.0133***	0.0124***	0.0115***	0.00974***
	(0.00585)	(0.00372)	(0.00257)	(0.00132)	(0.00229)
Change in log oil pr. (importer)	0.00444*	0.00521***	0.00573***	0.00626***	0.00723**
	(0.00237)	(0.00172)	(0.00189)	(0.00231)	(0.00343)
ZLB	-0.661***	-0.466***	-0.336***	-0.205*	0.0401
	(0.190)	(0.142)	(0.121)	(0.113)	(0.135)
Observations	1,363	1,363	1,363	1,363	1,363

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A30: Quantile regression estimates, commodity exporters vs importers, advanced economies

	Quantile				
Variables	(0.05)	(0.25)	(0.5)	(0.75)	(0.95)
Inflation	0.321***	0.414***	0.486***	0.571***	0.750***
	(0.0470)	(0.0403)	(0.0405)	(0.0487)	(0.0808)
Change in log real GDP	0.405***	0.277***	0.178**	0.0605	-0.187
	(0.0975)	(0.0748)	(0.0894)	(0.133)	(0.275)
Change in log neer	-0.0733*	-0.139***	-0.191***	-0.251***	-0.379***
	(0.0375)	(0.0336)	(0.0401)	(0.0576)	(0.103)
Change in log oil pr. (exporter)	0.0128	0.00800	0.00428	-0.000114	-0.00936
	(0.0139)	(0.0112)	(0.0126)	(0.0176)	(0.0327)
Change in log oil pr. (importer)	0.0244***	0.0262***	0.0275***	0.0291***	0.0325**
	(0.00673)	(0.00603)	(0.00674)	(0.00820)	(0.0130)
Not inflation targeter	1.718***	2.005***	2.229***	2.493***	3.050*
	(0.589)	(0.522)	(0.666)	(0.932)	(1.791)
Observations	3,075	3,075	3,075	3,075	3,075

Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A31: Quantile regression estimates, commodity exporters vs importers, EMEs

	Quantile				
Variables	(0.05)	(0.25)	(0.5)	(0.75)	(0.95)
Inflation	0.131*	0.294***	0.395***	0.493***	0.679***
	(0.0680)	(0.0531)	(0.0593)	(0.0758)	(0.119)
Change in log real GDP	0.347***	0.272***	0.225***	0.179***	0.0934
	(0.108)	(0.0625)	(0.0408)	(0.0405)	(0.0840)
Change in log neer	-0.0502*	-0.0377**	-0.0299**	-0.0223	-0.00798
	(0.0302)	(0.0158)	(0.0132)	(0.0191)	(0.0370)
Exchange rate peg	-0.924	-0.959*	-0.981***	-1.002***	-1.043**
	(0.880)	(0.524)	(0.332)	(0.217)	(0.455)
Peg * change in log neer	0.0449	0.0357	0.0299	0.0244	0.0138
	(0.0425)	(0.0307)	(0.0355)	(0.0526)	(0.0843)
Change in log oil price	0.00603**	0.00686***	0.00738***	0.00788***	0.00883***
	(0.00271)	(0.00180)	(0.00172)	(0.00195)	(0.00288)
ZLB	-0.527**	-0.384**	-0.295**	-0.210	-0.0465
	(0.217)	(0.168)	(0.138)	(0.135)	(0.149)
Observations	1,363	1,363	1,363	1,363	1,363

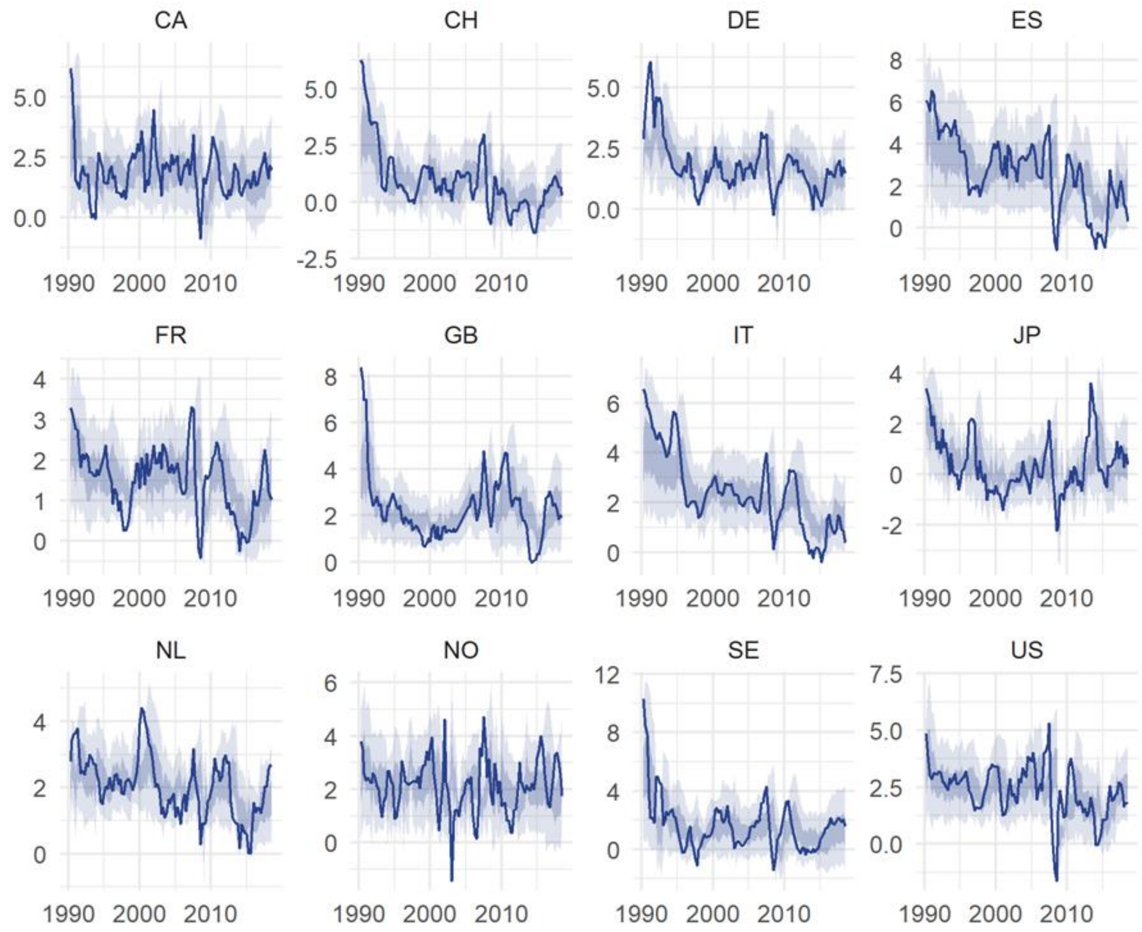
Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A32: Quantile regression estimates, model with exchange rate peg, advanced economies

Variables	(0.05)	(0.25)	Quantile (0.5)	(0.75)	(0.95)
Inflation	0.304***	0.399***	0.464***	0.547***	0.716***
	(0.0556)	(0.0435)	(0.0444)	(0.0528)	(0.0837)
Change in log real GDP	0.409***	0.267***	0.169*	0.0458	-0.207
	(0.0933)	(0.0712)	(0.0916)	(0.140)	(0.260)
Change in log neer	-0.0508	-0.126***	-0.178***	-0.243***	-0.377***
	(0.0355)	(0.0307)	(0.0377)	(0.0601)	(0.123)
Exchange rate peg	-1.270	-1.805***	-2.176***	-2.642***	-3.600***
	(0.872)	(0.698)	(0.698)	(0.829)	(1.357)
Peg * change in log neer	-0.117	-0.0512	-0.00540	0.0523	0.171
	(0.0973)	(0.0647)	(0.0543)	(0.0681)	(0.146)
Change in log oil price	0.0218***	0.0219***	0.0219***	0.0219***	0.0220**
	(0.00576)	(0.00454)	(0.00493)	(0.00632)	(0.0111)
Not inflation targeter	1.838***	2.308***	2.633***	3.043***	3.884**
	(0.683)	(0.509)	(0.640)	(0.996)	(1.910)
Observations	3,075	3,075	3,075	3,075	3,075

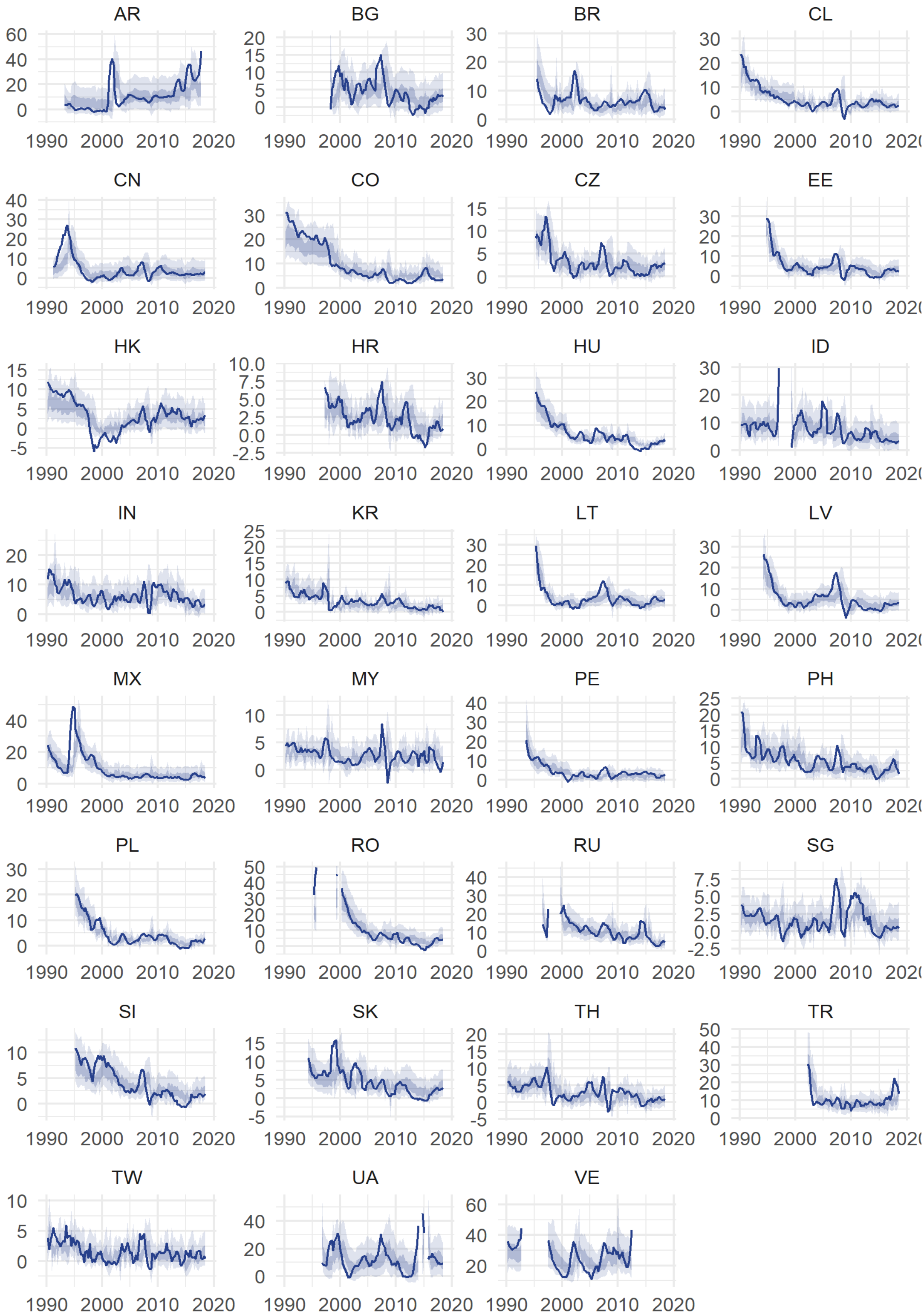
Note: Dependent variable is four-quarter-ahead year-on-year CPI inflation.
Bootstrapped standard errors clustered by country in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A33: Quantile regression estimates, model with exchange rate peg, EMEs



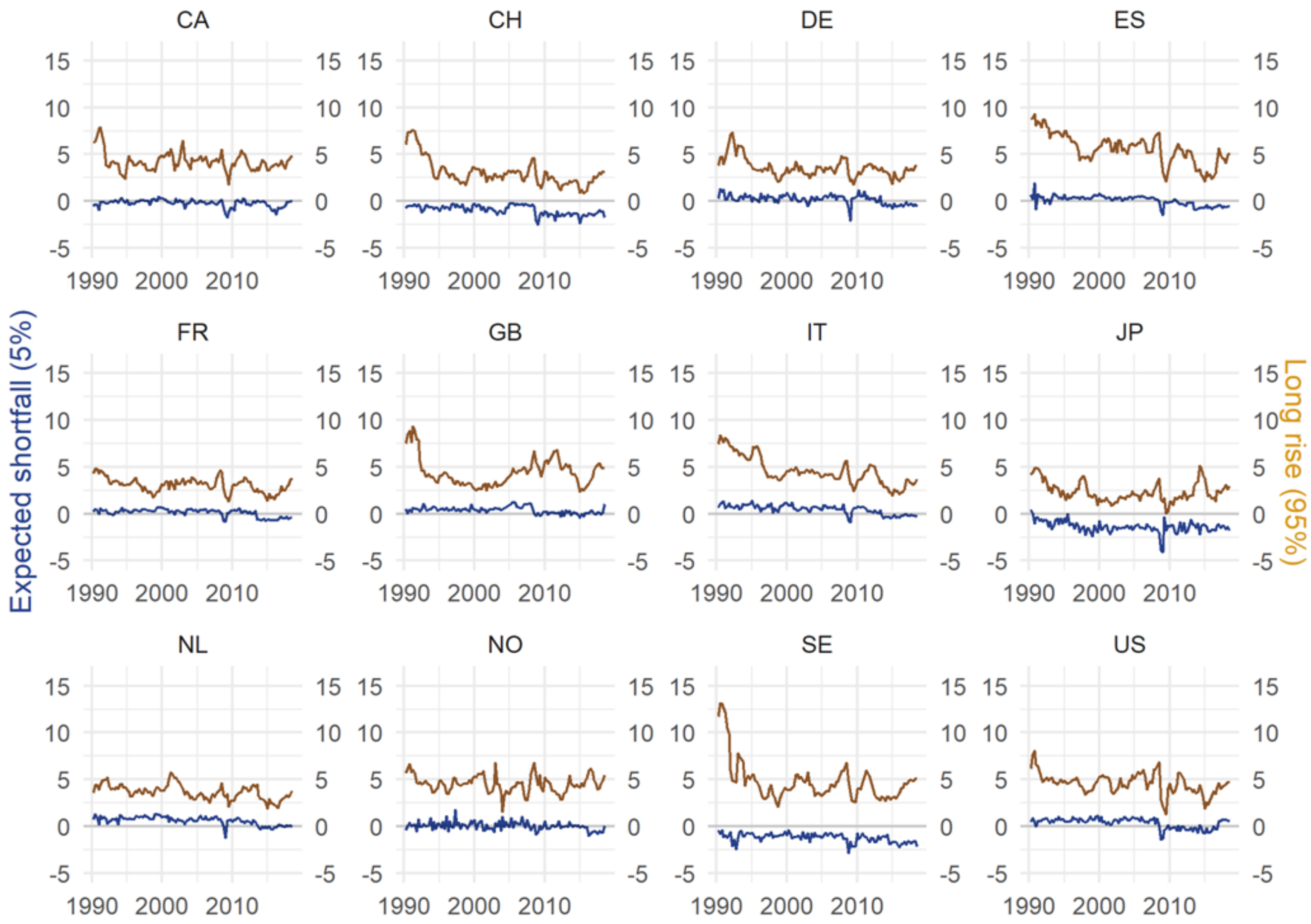
Note: The highlighted areas correspond to the 5, 25, 75 and the 95 percent quantiles. The solid line is four-quarter-ahead inflation. Country codes: CA = Canada; CH = Switzerland; DE = Germany; ES = Spain; FR = France; GBC = United Kingdom (CPI inflation); GBR = United Kingdom (RPI inflation); IT = Italy; JP = Japan; NL = Netherlands: NO = Norway; SE = Sweden; US = United States

Graph A1: Quantile conditional distributions, four-quarter-ahead inflation, advanced economies



Note: The highlighted areas correspond to the 5, 25, 75 and the 95 percent quantiles. The solid line is four-quarter-ahead inflation. Country codes: AR = Argentina; BG = Bulgaria; BR = Brazil, CL = Chile; CN = China; CO = Colombia; CZ = Czech Republic; EE = Estonia; HK = Hong Kong SAR; HR = Croatia; HU = Hungary; ID = Indonesia; IN = India; KR = Korea; LT = Lithuania; LV = Latvia; MX = Mexico; MY = Malaysia; PE = Peru; PH = Philippines; PL = Poland; RO = Romania; RU = Russia; SG = Singapore; SI = Slovenia; SK = Slovakia; TH = Thailand; TR = Turkey; TW = Chinese Taipei; UA = Ukraine; VE = Venezuela

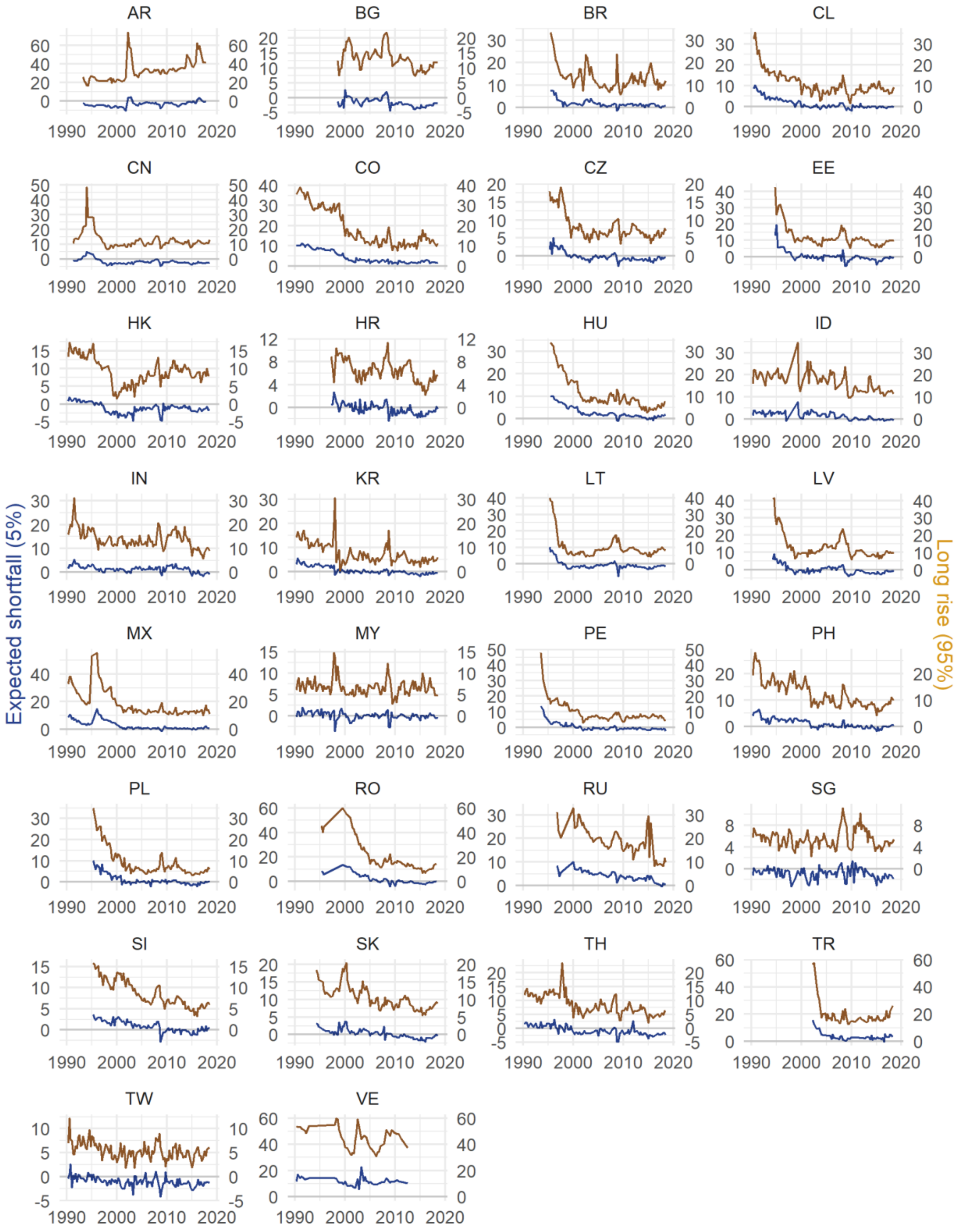
Graph A2: Quantile conditional distributions, four-quarter-ahead inflation, EMEs



Note: The expected shortfall (5%) is shown in blue and the expected longrise (95%) in red. Given a target probability p (we choose p = 5%), the shortfall SF and longrise LR are computed as:

$SF_{t+h} = \frac{1}{p}\int_0^p \hat{F}^{-1}_{\pi_{t+h|x_t}}(\tau|x_t)\, d\tau$ and $LR_{t+h} = \frac{1}{p}\int_{1-p}^1 \hat{F}^{-1}_{\pi_{t+h|x_t}}(\tau|x_t)\, d\tau.$

Graph A3: Inflation risks: expected shortfall and longrise, advanced economies



Note: The expected shortfall (5%) is shown in blue and the expected longrise (95%) in red. Given a target probability p (we choose p = 5%), the shortfall SF and longrise LR are computed as:

$SF_{t+h} = \frac{1}{p}\int_0^p \hat{F}^{-1}_{\pi_{t+h|x_t}}(\tau|x_t)\, d\tau$ and $LR_{t+h} = \frac{1}{p}\int_{1-p}^1 \hat{F}^{-1}_{\pi_{t+h|x_t}}(\tau|x_t)\, d\tau$.

Graph A4: Inflation risks: expected shortfall and longrise, EMEs

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