Bank of Japan Working Paper Series

The Term Structure of Inflation at Risk: A Panel Quantile Regression Approach

Yoshibumi Makabe*
yoshibumi.makabe@boj.or.jp

Yoshihiko Norimasa**
yoshihiko.norimasa@boj.or.jp

No.22-E-4
May 2022

Bank of Japan
2-1-1 Nihonbashi-Hongokucho, Chuo-ku, Tokyo 103-0021, Japan

* International Department
** International Department

The Term Structure of Inflation at Risk: A Panel Quantile Regression Approach*

Yoshibumi Makabe† and Yoshihiko Norimasa‡

May 2022

Abstract

This paper uses panel quantile regression to analyze the factors affecting inflation risks defined as the tail of the predictive inflation distribution. We construct a panel going back to the "Great Inflation" period (from the late 1960s) and include variables that capture not only downside risks, which many recent studies have focused on, but also upside risks to examine the developments in both upside and downside risks to inflation in the United States, Germany, and the United Kingdom. Our analysis shows that unit labor costs and real government spending have a significant effect on the upward risks to inflation. We also find that the effect of import prices on inflation risks is short-lived, while the effect of real government spending and unit labor costs persists over the medium term. These results also show that the term structure of the effect on inflation risks differs depending on the factor involved.

JEL Classification: C21, E27, E31

Keywords: Inflation risk, panel quantile regression, term structure

* We would like to thank Kosuke Aoki, Sohei Kaihatsu, Yoshitaka Ichise, and members of the staff of the Bank of Japan for their helpful comments. The views expressed in this paper are those of the authors and do not represent the official views of the Bank of Japan. Any possible errors are the authors' responsibility.

† International Department, Bank of Japan (e-mail: yoshibumi.makabe@boj.or.jp).

‡ International Department, Bank of Japan (e-mail: yoshihiko.norimasa@boj.or.jp).

1 Introduction

With demand in the United States and many European countries recovering rapidly following the resumption of economic activity in the wake of the crisis brought about by the COVID-19 pandemic, inflation is rising, partly due to supply constraints caused by logistics delays and labor shortages, and partly due to rising energy and food prices. As noted by the International Monetary Fund (2022), this increase in inflation in the United States and many European countries has been larger and more protracted than initially expected, increasing uncertainty over future inflation rates.

It is worth remembering that many studies and reports published in the early stages of the pandemic in the first half of 2020 expected that the pandemic would exert deflationary pressure on the economy as the introduction of strict public health measures would reduce demand (Blanchard, 2020; IMF, 2020). While it is easy to point out the errors in such forecasts with the benefit of hindsight after observing the current high level of inflation, the magnitude of these forecast errors illustrates how difficult it is to forecast future inflation rates in the context of the recovery from the global pandemic.

The difficulty in forecasting future inflation in the current phase stems from the fact that business cycle fluctuations are greatly amplified by developments in the pandemic and government interventions (public health measures and large-scale fiscal policies), and that structural factors such as the vulnerability of global supply chains (such as logistics disruptions) and the labor force exit triggered by the pandemic must be taken into account simultaneously. On the other hand, looking back to before the pandemic, during the "Great Moderation" that started in the early 1980s, inflation in advanced economies followed a gradual downward trend and, especially from the 1990s, was very stable, so that interest instead focused on the causes for such low inflation (see, e.g., Coibion and Gorodnichenko, 2011; Heise, Karahan, and Şahin, 2021; Eggertsson, Mehrotra, and Robbins, 2019). Therefore, in the context of this complex interplay of factors that have contributed to the structural decline in inflation over the past three decades and the various factors that have emerged since the pandemic, it is necessary to reassess inflation risks in the United States and many European countries in terms of their determinants and persistence.

Recent research on inflation risk has been conducted against the background of the downward trend in inflation over the past three decades in advanced economies, particularly in the United States and Europe, and has concentrated on (1) the downside risks to inflation posed by financial imbalances and vulnerabilities based on the lessons from the global financial crisis, and (2) the downside risks to inflation posed by the effective lower bound on policy rates (see, e.g., López-Salido and Loria, 2020; and Banerjee et al., 2020). It is therefore only natural that the data analyzed in these studies only cover on the period from the late 1980s, when inflation rates began to stabilize. However, given current developments in inflation in the wake of the pandemic, especially in the United States, it is becoming increasingly important to conduct analyses that include the "Great Inflation" period from the 1960s to the 1980s, when upside risks to inflation were a problem, in order to discuss the upside and downside risks to inflation going forward.

Based on these considerations, we construct a long-term time-series panel spanning the period from the 1960s onward for the United States, Canada, Japan, and nine European countries and estimates the predictive inflation distribution using quantile regression models. We define the tail of the conditional predictive distribution of inflation as inflation risks and examine its behavior and determinants. Further, we estimate the "term structure" of the effect of each factor on inflation risks, which allows us to quantitatively examine the persistence of the effect.

The remainder of this paper is organized as follows. Section 2 reviews previous studies relevant to this paper and summarizes the positioning and contributions of this paper within that context. Section 3 describes the data and empirical approach used in the empirical analysis. Section 4 presents and interprets the estimation results obtained. Section 5 concludes.

2 Literature Review and Contributions of This Paper

Previous research on the measurement of inflation risk has been conducted from both a time-series and a financial engineering perspective. Studies from a time-series perspective generally regard inflation risks as the error in forecasting the inflation rate and have focused on analyzing the statistical properties of such forecast error. Specifically, the forecast error of inflation typically is specified as a stochastic volatility model (see, e.g., Engel, 1983; Grier and Perry, 1998; Stock and Watson, 2007), and the parameters estimated in the model are then used to examine the distributional characteristics of, and time-series variations in, the forecast error (i.e., inflation risks). Such studies are undoubtedly useful if our main interest is to understand the statistical properties of inflation forecast errors. However, since the factors affecting risks defined as forecast errors cannot be identified, the econometric results are difficult to interpret and the implications for the conduct of monetary policy would be unclear. Moreover, since the direction of risks depends on the assumptions underlying the model, the usefulness of this approach as a way to measure risk is also limited.[1] On the other hand, studies from a financial engineering perspective have focused on measuring inflation risk premia (inflation risks) using transaction prices in financial markets. For example, using pricing models to measure inflation risk premia based on the market prices of treasury inflation-protected securities (TIPS) and inflation swaps, it is possible to obtain market-implied information on the direction and the uncertainty of future inflation.[2] Furthermore, if an interest rate swaption market with some liquidity exists, using pricing models based on option prices, it is possible to estimate the asymmetric future inflation distribution (Kitsul and Wright, 2013; Fleckenstein, Longstaff, and Lustig, 2017) and understand the shape of the entire distribution. However, as with time series models, it is difficult in these studies to directly identify the factors affecting risks,[3] and there are challenges in risk measurement, since the expected inflation distribution extracted from option prices is measured under the risk-neutral measure Q, so that additional assumptions are required to transform the risk-neutral distribution to one under the physical measure P.[4]

To address the above issues surrounding the measurement of risks such as the verification of the asymmetric properties of risks and the identification of factors affecting risks, an approach that measures the predictive inflation distribution using quantile regression models has recently attracted growing attention. While ordinary regression analysis estimates the conditional expectation of the mean, quantile regression makes it possible to examine the shape of the entire distribution through the estimation of quantile points in addition to the conditional mean expectation. Another advantage is that since the predictive inflation distribution estimated by quantile regression – unlike the distribution of expected inflation measured using a pricing model based on financial

---

[1] Inflation forecasts are obtained through univariate models using the own lag of the inflation rate (see, e.g., Grier and Perry, 1998; and Stock and Watson, 2007) or through multivariate models using specifications such as the Phillips curve (e.g., Engel, 1983; Amisano and Giacomini, 2007). In particular, using regime switching models and Bayesian estimation techniques, Amisano and Giacomini (2007) report density forecasts that do not depend on the normal distribution.

[2] For details, see the survey by Kupfer (2018).

[3] Fleckenstein, Longstaff, and Lustig (2017), for example, identify risk factors by examining the relationship between estimated inflation risk premia and financial and economic variables not included in the estimation model, and find that financial sector credit and liquidity risks as well as the unemployment rate are positively correlated with the probability of deflation. Meanwhile, an example of a study examining the relationship between inflation risk premia and economic variables in a single framework is the study by Hördahl and Tristani (2014), who find that in the United States and the euro area cost-push shocks change inflation risk premia more than demand shocks.

[4] Fleckenstein, Longstaff, and Lustig (2017), based on additional assumptions, compute the distribution of inflation expectations under the physical measure.

market transaction prices – is based on real-world probabilities, it is easier to interpret. One of the first studies focusing on statistics other than the mean is that by Manzan and Zerom (2013), who used quantile regression to partially measure the predictive inflation distribution. Subsequently, the method of measuring GDP growth-at-risk using the conditional predictive distribution of GDP growth proposed by Adrian, Boyarchenko, and Giannone (2019) was used for the analysis of inflation by Banerjee et al. (2020) and López-Salido and Loria (2020), marking the start of the measurement of the entire inflation distribution and the more detailed analysis of asymmetries and factors of inflation risks. For example, using a quantile regression model with time-varying parameters, Korobilis et al. (2021) examine inflation risks and find that financial variables play an important role in determining inflation risks.

Previous studies on inflation risks using quantile regression have mainly been interested in understanding developments during the "Great Moderation" in advanced economies. As a result, and based on the lessons learned from the global financial crisis, they have primarily focused on examining the effects of financial imbalances and vulnerabilities on downside risks to inflation and on measuring the downside risks to inflation posed by the effective lower bound on the policy rate. However, in the wake of the pandemic, inflation has been rising rapidly, especially in the United States and many European countries, and understanding the upside and downside risks to future inflation has become an urgent issue for policymakers. In this study we therefore use long-term panel data for the period going back to the 1960s, which includes past episodes of high inflation.

In terms of the data used, most recent studies on inflation risks have relied on data for a single country, in many cases the United States, or, in the case of panel data for advanced economies, for somewhat shorter periods starting from the late 1980s (e.g., López-Salido and Loria, 2020; Banerjee et al., 2020). This paper takes a somewhat different approach: while recognizing that the effects of economic and financial variables on inflation risks may differ from country to country, we use fixed effects estimators from quantile regressions to extract the average effect across countries in the data set and examine the factors affecting inflation risks based on cross-sectional and time-series variations in a range of explanatory variables.

On the one hand, this ensures stability of the estimates by increasing the cross-sectional dimension by including not only the United States but also European and other countries; on the other hand, constructing time series data going as far back as the late 1960s covering as long a period as possible also addresses the statistical issues involved in obtaining fixed effect estimators through quantile regression. That is, when obtaining fixed effects estimators based on the model proposed by Koenker (2004) that we use in this paper, the number of observations in the time-series dimension must be sufficiently large relative to the number of observations in the cross-section dimension to ensure the statistical stability of the estimators (see Besstremyannaya and Golovan, 2019).

Moreover, in quantile regression it is important to set explanatory variables in a parsimonious manner since coefficients are estimated for each quantile. Although the number of explanatory variables in this paper is relatively large due to the addition of economic variables to capture inflation risks, the addition of variation from the time-series average of each country in the panel data is also expected to facilitate identification.

In addition to canonical economic variables used for the estimation of the Phillips curve and employed in previous studies, such as lagged values of the inflation rate and the output gap (or unemployment rate gap), we include variables representing financial imbalances and vulnerabilities that previous studies have regarded as important in capturing downside risks (Banerjee et al., 2020; López-Salido and Loria, 2020) as well unit labor costs and real government spending in our quantile regression estimation of inflation risks. Of these, unit labor costs were added based on the empirical finding of Mehra (2000), who estimated the conditional mean of prices given wages and, using data for the United States, found spillovers from wages to prices during periods of high inflation such as the "Great Inflation" period. Moreover, we included real government spending based on the experience of the United States in the mid-1960s, at the beginning of the "Great Inflation," when increased fiscal spending to finance the Vietnam War triggered high inflation, as pointed out by Meltzer (2005). This point may be important from the perspective of quantitatively assessing the impact of the expansion of U.S. fiscal spending since the outbreak of the pandemic on inflation risks, something that Summers (2021) and Blanchard (2020) have expressed concern about. Our findings show that both higher unit-labor costs and higher real government spending significantly increase the upside risks to inflation and that this impact tends to be persistent.

Meanwhile, considering whether inflation risks are present is an important issue in the conduct of monetary policy, and another contribution of this paper is that it examines the factors affecting inflation risks in terms of their "term structure". Looking at previous studies, while Korobilis et al. (2021) measure inflation risks for two forecasting periods, one year ahead and three years ahead, their focus is on improving forecasting accuracy by including financial variables in the model and allowing coefficients to vary over time, and they do not examine the term structure of factors affecting inflation risks. Thus, a key aim of this paper is to examine the term structure of factors affecting inflation risks by combining quantile regression and the local projections approach developed by Jordà (2005). This approach has been employed in measuring the risks to various economic and financial variables (Linnemann and Winkler, 2016; Loria, Matthes, and Zhang, 2019; Jordà et al., 2020), and Adrian et al. (2021) and Aikman et al. (2019), for example, show empirically that the effect of financial variables on GDP growth-at-risk varies by quantile and projection period, and that the accumulation of financial imbalances increases the downside risks to medium- and long-term growth. Against this background, our study shows empirically that (1) a substantial increase in import prices boosts the upside risks to inflation in the short run but the effect is not persistent in the medium run, and (2) increases in unit labor costs and real government spending raise the upside risks to inflation in the medium run in a persistent manner (with a small short-term effect), indicating that factors differ in terms of the term structure of their impact on inflation risks.

3 Data and Empirical Approach

3.1 Data and descriptive statistics

The unbalanced panel data we use for our analysis cover the United States, Canada, Japan, and nine European countries.[5] The data are quarterly, and the estimation period runs from 1965Q1 to 2016Q4. That is, the estimation period excludes the period of the COVID-19 pandemic from 2020 onward. It ends with 2016Q4 since inflation rates up to 12 quarters ahead are required when estimating the term structure of the effect of explanatory variables on inflation risks.

Let us start by looking at the summary statistics of the data used in the empirical analysis (Table 1). For inflation, the mean is higher than the median, and a similar pattern can be observed for unit labor costs and import prices. The characteristics of these variables over time suggest that although they are stable for most of the observation

[5] Specifically, the countries included and the period for which data for each country are available are as follows: Canada (1971Q1–2016Q4), France (1969Q4–2016Q4), Germany (1971Q1–2016Q4), Italy (1971Q1–2016Q4), Japan (1965Q1–2016Q4), Netherlands (1978Q1–2016Q4), Norway (1996Q1–2016Q4), Spain (1981Q1–2016Q4), Sweden (1981Q1–2016Q4), Switzerland (1991Q4–2016Q4), United Kingdom (1971Q4–2016Q4), and United States (1965Q1–2016Q4).

period (normal times), there are a small number of periods of large increases. On the other hand, we find that the mean and median values are generally similar for real government spending, the persistence of credit overheating (explained below), and the output gap.

Historically, the key period of heightened global inflation uncertainty was the period of "Great Inflation" from the late 1960s to the early 1980s, when inflation rates rose to extreme levels. Many studies on the reasons for the high inflation and heightened inflation risks at that time point to the de-anchoring of inflation expectations as one important factor (Orphanides and Williams, 2005; Leduc, Sill, and Stark, 2007). In light of these findings, we divide our observations into periods in which a nominal anchor, such as a fixed exchange rate regime or inflation targeting policies, which are thought to anchor inflation expectations, were in place and periods in which no such anchor was in place and then compare the summary statistics.[6]

Observations are divided as falling into either type of period following Mishkin (1999), who treats the following as periods in which a nominal anchor was in place: (1) the period when a fixed exchange rate system was in place under the Bretton Woods system and (2) periods when inflation targeting policies were implemented.[7]

In period in which a nominal anchor was in place, the mean and median inflation rates were lower than in periods when no anchor was in place. Moreover, the mean and median values were more or less of the same size. This suggests that during periods when a nominal anchor is in place, the inflation rate tends to be low, and even when the inflation rate rises, the magnitude of the increase tends to be small and stable. However, since similar tendencies are observed for unit labor costs and import prices, it is not possible to conclude from the summary statistics alone whether the factors that contributed to the suppression of inflation were the introduction of a nominal anchor or economic variables

[6] For example, Bordo and Eichengreen (2013) point out that the fixed exchange rate regime under the Bretton Woods system contributed to the stability of the inflation rate. Meanwhile, Gürkaynak, Levin and Swanson (2010), Beechey, Johannsen, and Levin (2011) and Davis (2014) report that the introduction of inflation targeting policies increased the degree of anchoring of inflation expectations among economists and in financial markets.

[7] Mishkin (1999) also classifies monetary targeting as one type of nominal anchor. However, since monetary targeting implies the use of the quantity of money instead of the interest rate as the guiding target of monetary policy, and in some respects only represents a different policy instrument, we do not classify periods of monetary targeting as periods in which a nominal anchor was in place. Moreover, we only treat periods in which inflation targeting was officially adopted as nominal anchor periods. For example, for the United States, some studies argue that the Federal Reserve had started implicit inflation targeting before its "official" introduction as a policy in 2012 (Leigh, 2008; Ireland, 2007). However, for our analysis, we only regard the period from the "official" introduction of inflation targeting in 2012 as the time when a nominal anchor was in place.

such as unit labor costs and import prices. It is therefore necessary to construct and quantitatively examine a model for measuring inflation risks that includes economic variables such as unit labor costs while controlling for whether a nominal anchor was in place.

Next, using data for the United States, we examine the dynamics in uncertainty regarding future inflation, following the measurement methods used in previous studies, that is, by examining (1) forecast errors from a time series perspective (Stock and Watson, 2007) and (2) inflation risk premia from a financial engineering perspective (Kitsul and Wright, 2013). The results are shown in Chart 1. The results based on the former approach suggest that periods in which the average of inflation risks increased are the "Great Inflation" period, the period of high commodity prices before the global financial crisis, and the period since the outbreak of the COVID-19 pandemic.[8] However, the drivers of the increase in inflation risks clearly differed: while permanent innovations were the main factor underlying the increase in the average of inflation risks during the "Great Inflation," transitory innovations were the main factor during the period of high commodity prices before the global financial crisis and since the outbreak of the pandemic. That said, whereas the impact of permanent innovations remained small for a long time during the Great Moderation, it has recently been on the rise. Turning to the results based on the latter approach, the observation period starts only in 2010 due to data limitations. The chart shows that downside risks increased sharply immediately after the outbreak of the pandemic and then declined sharply, while upside risks have increased recently and remain at a high level. As noted above, while these indicators can capture the rise in inflation risks (both upside and downside), they do not tell us what the drivers behind this rise are, which is why our aim is to clarify the links between the dynamics in inflation risks and the factors underlying such dynamics.

3.2 Empirical approach

This section describes the quantile regression approach, the econometric technique we use for quantitatively examining the various factors (explanatory variables) that affect

[8] Stock and Watson (2007) viewed the inflation rate as a stochastic process that can be decomposed into a permanent component and a transitory component and specified both stochastic processes to follow a stochastic volatility model. That is, the logarithm of the volatility (variance) of each follows an AR(1) model. The volatility of the permanent component (permanent innovation) and the volatility of the transitory component (transitory innovation) are then estimated for the forecast error of the inflation rate. The average value of inflation risks here represents the simple average of the estimates of both volatilities (expressed by standard deviations).

inflation risk, and explains the conditional predictive distribution of inflation derived from the estimates. Specifically, the entire conditional inflation distribution is calibrated employing the following two steps: (1) we estimate the effect of the explanatory variables at each quantile using panel quantile regression, and (2) approximate the estimated quantile function with a skewed *t*-distribution. In the predictive inflation distribution thus obtained, we define the upper 10th percentile and lower 10th percentile as the upside and downside risks to inflation, denoted by IaR_{90} and IaR_{10}, where "IaR" stands for "inflation at risk." This calibration method is similar to that used by Adrian, Boyarchenko, and Giannone (2019) in the calibration of the conditional distribution of GDP growth. Moreover, we also use the probability of the inflation rate being above or below a certain threshold, as calculated by López-Salido and Loria (2020) and Kitsul and Wright (2013), as the upside or downside risks to inflation respectively.

Previous studies using quantile regression to measure the risks to economic variables can be categorized into those using panel data and those using only time series data (i.e., data with one series in the cross-section dimension). When, as in this study, panel data are used for analyses with fixed effects estimators, what we seek to examine is not the cross-country heterogeneity in the effect of the various drivers of inflation risks but the contribution of time-series and cross-country variations in explanatory variables to the dynamics in inflation risks given the conditional mean of the effects of such variable across countries. As mentioned above, one of the advantages of using panel data to obtain fixed effects estimators is that it reduces correlations among explanatory variables and allows us to accurately identify the average effects across countries in the data. Taking this advantage into account, we use panel data for twelve advanced economies to alleviate the following problems. First, different economic variables often comove due to business cycle fluctuations, so that using data for a single country only is likely to make the identification of the effect of explanatory variables less accurate than when using data for multiple countries. Second, although it is important in quantile regression to set explanatory variables in a parsimonious manner in terms of the degrees of freedom since coefficients are estimated for each quantile, we include not only the canonical explanatory variables also used in other studies but also additional variables capturing the upside risks to inflation, so that we have a larger number of coefficients.

Our quantile regression approach consists of the following two steps.

Step 1

The first step consists of using panel quantile regression to estimate the quantile function of the future inflation rate (h quarters ahead, year-on-year rate of change in consumer prices, $\pi_{i,t+h}$). Given the realized values of the explanatory variables ($X_{i,t}$), the conditional quantile of the future inflation rate can be expressed as follows:

$$\hat{Q}\left(\tau;\pi_{i,t+h}|X_{i,t}\right) = X_{i,t}\widehat{\beta_h^\tau}$$

where i denotes the country and $\tau \in (0,1)$ the quantile point. We conduct the panel quantile regressions with the fixed effects by Koenker (2004)[9] and explanatory variables selected based on the considerations described in the previous section:

$$\begin{aligned}\hat{Q}\left(\tau;\pi_{i,t+h}\right) = \widehat{\beta_{0,h}^\tau}\Delta GovtSpend_{i,t} + \widehat{\beta_{1,h}^\tau}\Delta ULC_{i,t} \\ +\widehat{\beta_{2,h}^\tau}\pi_{i,t}^{imp} + \widehat{\beta_{3,h}^\tau}\pi_{i,t}^{imp}\cdot I_{i,t}^{imp} + \widehat{\beta_{4,h}^\tau}\overline{I_{i,t}^{CreditGap}} \\ + \widehat{\beta_{5,h}^\tau}\bar{\pi}_{i,t} + \widehat{\beta_{6,h}^\tau}ygap_{i,t} + \widehat{\beta_{7,h}^\tau}NomAnchor_{i,t} + \widehat{\gamma_{h,i}}\end{aligned}$$

Table 2 shows the expected signs for the coefficients for each quantile and forecast period (short-term and medium-term).[10] Starting with $\Delta GovtSpend_{i,t}$, this is the year-on-year rate of change in real government spending (in percent). Although it is not certain whether real government spending pushes up future inflation risks in the short run, it is likely to increase inflation risks in the medium run by boosting the economy. In addition, since, according to menu cost models, price adjustments are easier when inflation is high, an increase in demand through government spending will make it more likely for inflation at the macro-level to rise even further. Therefore, in terms of the expected sign for each quantile, the higher the quantile, the stronger the effect of real government spending on inflation risks is expected to be. Consequently, statistically significant positive coefficients are more likely to be obtained for the upper quantiles than the lower and middle quantiles.

Next, $\Delta ULC_{i,t}$ is the year-on-year rate of change in unit labor costs (in percent). In the debate over higher inflation since the pandemic, attention is once again focusing on the wage-price relationship. If nominal wages rise more than labor productivity (i.e., unit labor costs rise), this would act as a cost-push shock in the direction of pushing up the upside risks to inflation in the short and medium term. However, the effect of this explanatory variable may vary depending on the circumstances at the time. For instance, Peneva and Rudd (2017) argue that during the "Great Inflation" period, when inflation expectations were not anchored, the pass-through from wages to prices was large. In

[9] The fixed effects obtained following Koenker (2004) are independent of the quantile point.
[10] For a detailed description of the data used in the estimations, see Appendix 1.

contrast, according to Heise, Karahan, and Şahin (2021), empirical evidence for the United States shows that during the "Great Moderation" period, the higher share of imports from China and the increase in domestic market concentration reduced the pass-through from wages to prices, especially in the goods market, so that the impact of wage increases in terms of pushing up the aggregate inflation rate was small. Meanwhile, as with real government spending, based on the menu cost model, the effect of unit labor costs on inflation risks is expected to be larger at the upper quantile points.

Moreover, future inflation is also affected by supply shocks from abroad through imported goods. Since such shocks can be captured by changes in exchange rates as well as changes in commodity prices, as represented by crude oil, the year-on-year rate of change in import prices ($\pi_{i,t}^{imp}$) is added as an explanatory variable as a proxy variable.[11] In addition, taking into account that small increases in import prices are likely to be absorbed by firms and hence unlikely to be passed on to consumer prices, we also include the interaction term of the change in import prices and a dummy variable ($I_{i,t}^{imp}$) that takes 1 when the rate of increase in import prices exceeds the historical average to examine the degree of pass-through of import prices to consumer prices. Regarding the effect on future inflation risks, if the underlying factor is a supply shock such as a commodity price shock, the effect is likely to be transitory, and while the short-term effect is positive, the medium-term effect may be small and/or not statistically significant. As for the effect at each quantile, based on the menu cost model, the effect is expected to be larger the higher the quantile.

In addition, since the global financial crisis, studies have focused on examining the effects of financial variables representing financial imbalances and vulnerabilities on the future inflation rate.[12] We therefore also include as an explanatory variable the total credit-to-nominal GDP ratio, which has been shown to be useful as an early warning indicator for financial crises. In doing so, following the Basel Committee on Banking

[11] López-Salido and Loria (2020) use import prices as explanatory variables, while Banerjee et al. (2020) use oil prices and nominal effective exchange rates as explanatory variables. Because we use long-term time series data that include the 1960s, when fixed exchange rates were maintained under the Bretton Woods regime, we use import prices as our explanatory variables, since nominal effective exchange rates did not change during that period.

[12] The relationship between macroeconomic and financial variables has been the subject of numerous studies, notably Kiyotaki and Moore (1997) and Bernanke, Gertler, and Gilchirst (1999). Moreover, and those theoretical studies have highlighted the importance of channels through which the aggregate economy is affected by a contraction in credit caused by stress in the financial sector (damaged borrower balance sheets, a decline in the value of collateral, etc.). Empirical studies, such as Adrian, Boyarchenko. and Giannone (2019), have also shown that the role of financial variables is important when considering the risks to real variables such as GDP growth.

Supervision (2010) and Ito et al. (2014), we first create a dummy variable ($I_{i,t}^{CreditGap}$) that takes 1 when the credit-to-GDP gap, that is, the gap between the total credit-to-nominal GDP ratio and its trend, exceeds a certain threshold. The persistence with which the dummy variable continues to take 1 until time t can be expressed by calculating the backward moving average of the dummy variable. Therefore, in the estimation model, we calculate the three-year (12-quarter) backward moving average[13] and use this as an explanatory variable to represent the accumulation of financial imbalances, which we refer to as the persistence of credit overheating hereafter. The more persistent such financial imbalances are, the larger the risk of a financial crisis is likely to be, so that the effect on inflation risks is likely to be negative, regardless of the quantile. On the other hand, the accumulation of financial imbalances may have a positive effect on inflation risks in the short term because of the risk of an overheating of the economy. Therefore, the expected sign for short-term inflation risks is difficult to predict a priori. However, when inflation falls substantially, nominal interest rates are also expected to fall. Given that in this case the room for monetary policy to respond to negative shocks to the economy is likely to be more limited, we expect that the lower the quantile, the earlier the negative effect of financial imbalances is likely to occur and the greater the effect on downside inflation risks is likely to be. In sum, in the short term, the effects are expected to be negative at the lower quantiles, while the expected sign cannot be determined a priori for the middle and upper quantiles. In the medium term, a negative effect is expected regardless of the quantile.

We control for autocorrelation in the inflation rate using the lag term of the inflation rate ($\bar{\pi}_{i,t}$, 2-period backward moving average) and for business cycle factors not captured by the above explanatory variables using the output gap ($ygap_{i,t}$). These are the canonical explanatory variables used in Phillips curve estimations and in previous studies such as López-Salido and Loria (2020). On the other hand, inflation expectations, which are an important component of the New Keynesian Phillips curve, are not used in our estimation due to data constraints.[14] We control for inflation expectations using a dummy variable

[13] To be precise, the variable is defined as follows:

$$\overline{I_{i,t}^{CreditGap}} = \begin{cases} \frac{1}{12}\sum_{p=0}^{11} I_{i,t-p}^{CreditGap} & if \quad I_{i,t}^{CreditGap} = 1 \\ 0 & otherwise \end{cases}$$

[14] In previous research on inflation risks using panel data, another study not employing inflation expectations as an explanatory variable is Banerjee et al. (2020). However, the estimation period in their study, which is from 1990Q1 to 2019Q1, coincides with the Great Moderation period. Therefore, if inflation expectations were more or less anchored during this period, controlling for inflation expectations to derive the fixed effects estimator, which is calculated using the deviation from the mean of each variable, may not be necessary. On the other hand, since the analysis in this paper uses

for periods in which a nominal anchor was in place ($NomAnchor_{i,t}$), which previous studies have shown to have a certain effect on the stability of inflation expectations. Specifically, we add a dummy variable that takes 1 for period in which the Bretton Woods fixed exchange rate system or an inflation targeting policy were in place, where such periods are identified as described in Section 3.1.

Step 2

In the panel quantile regression in Step 1, the conditional predictive quantile function of inflation is estimated. Intuitively, by estimating a large number of quantiles and linking the estimates for each quantile, it would be possible to obtain the entire predictive inflation distribution. However, the predictive distribution of inflation estimated in this manner (the empirical distribution) generally does not satisfy the properties of the probability density function due to estimation errors. We therefore derive a smooth predictive distribution that satisfies the properties of the probability density function by fitting the empirical distribution to a skewed *t*-distribution. Specifically, we approximate to the following skewed *t*-distribution based on Azzalini and Capitanio (2003), the properties of which are determined by four parameters $(\mu, \sigma, \alpha, \nu)$:[15]

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

where $t(\cdot)$ and $T(\cdot)$ denote the probability density function and the cumulative distribution function of Student's *t*-distribution, respectively. We use the algorithm proposed by Azzalini (2021) for calculating the skewed *t*-distribution. We calibrate the parameters $\{\mu, \sigma, \alpha, \nu\}$ of the skewed *t*-probability density function f to minimize the sum of squares of the distance between the quantile function estimated in Step 1, $\hat{Q}(\tau; \pi_{i,t+h})$, and the quantile function of the skewed *t*-distribution $F^{-1}(\tau; \mu, \sigma, \alpha, \nu)$ as shown below.[16] In doing so, we calibrate the parameters to minimize the distance at the seven quantile points ($\tau = \{0.05, 0.10, 0.30, 0.50, 0.70, 0.90, 0.95\}$).

data from the late 1960s onward, which includes periods of high inflation, controlling for inflation expectations would be highly desirable.

[15] μ is the location parameter, σ is the scale parameter, α is the shape parameter, and ν is the fatness parameter.

[16] When fitting the skewed *t*-distribution to the estimated conditional distribution, the approximation error and the shape of the conditional distribution differ substantially depending on the number of quantile points to be matched. For this reason, care needs to be taken when conducting analyses and interpreting results using the fitted conditional distribution only.

$$\{\hat{\mu}, \hat{\sigma}, \hat{\alpha}, \hat{\nu}\} = \underset{\mu,\sigma,\alpha,\nu}{\operatorname{argmin}} \sum_{\tau} \left(\hat{Q}(\tau; \pi_{i,t+h} | X_{i,h,t}) - F^{-1}(\tau; \mu, \sigma, \alpha, \nu) \right)^2$$

4 Estimation results

In this section, we start by reviewing the results of the quantile regression for each quantile to examine the effects of the various factors (explanatory variables) discussed in the previous section on inflation risks. Next, we provide an interpretation of the effect of each factor on inflation risks by presenting the results of the term structure estimated for the forecast period (short-term and medium-term). We then assess the dynamics of the indicators capturing inflation risks, which we define quantitatively in the latter part of the section, for the United States, Germany, and the United Kingdom. Moreover, we extend our basic model to conduct further analyses of the role of labor costs and real government spending, which have become increasingly important in light of economic developments since the outbreak of the pandemic, and the implications of the results are also explained.

4.1 Effect on short-term inflation risks

We first examine the marginal effects of the explanatory variables that affect one-year ahead (short-term) inflation for each quantile. Chart 2 shows the estimated marginal effects with regard to each explanatory variable on the vertical axis and arranges them by quantile on the horizontal axis, with the shaded areas showing the confidence intervals calculated using the block bootstrap method.[17]

The marginal effect of real government spending is larger at the upper quantiles than the medium quantiles, as shown in Chart 2(a). This implies that in phases of higher inflation, an increase in government spending has a greater impact on the inflation rate (compared to normal times), implying a greater impact on the upside risks to inflation. The following mechanisms can be interpreted as operating behind this. First, based on the menu cost model, when inflation is high, the potential costs for firms to adjust prices are smaller, making actual price adjustments more likely. Therefore, if an increase in

[17] To retain the autocorrelation structure in the time-series dimension, sampling was conducted 5,000 times, allowing for overlap, using eight consecutive quarters as blocks. See also Appendix Tables A1.1 and A1.2 for estimation results.

government spending increases the inflation rate through higher demand, the macro inflation rate is also likely to increase further due to more frequent price adjustments. Note that Blanchard (2020) highlights the risk that an excessive increase in government debt levels may lead to higher inflation. We empirically test the validity of this argument in Section 4.4 by extending the model to include an interaction term for real government spending conditional on the state of outstanding government debt.

Next, Chart 2(b) indicates that the higher the quantile, the larger is the marginal effect of unit labor costs on inflation risks. This implies that the pass-through from wages to prices is greater during periods of higher inflation, which implies a greater impact on the upside risks to inflation. These results are consistent with those reported by Mehra (2000). However, recent studies by Heise, Karahan, and Şahin (2021), Bobeica, Ciccarelli, and Vansteenkiste (2019), Peneva and Rudd (2017) and others empirically show that the pass-through from wages to prices has weakened since the 1990s and argue that reasons for this are the stabilization of inflation expectations and the increased dependence on trade due to globalization.[18] Since the "Great Moderation" also coincided with a period of low and stable inflation, in Section 4.4 we also extended the model to examine the effect of unit labor costs when controlling for the level of the import ratio as a proxy variable for trade dependence.

Regarding the marginal effect of import prices, when import prices rise at a rate far above the average rate of increase, the marginal effect is greater the higher the quantile point (as shown by the red line in Chart 2(c)). This can also be explained by the menu cost model, according to which it is easier to adjust prices during periods of high inflation. Looking at previous studies on the link between prices and exchange rates, which affect import prices, our findings are consistent with the empirical results of Gagnon and Ihrig (2004) and Devereux and Yetman (2010), who find that the pass-through from exchange rates to prices is greater during phases of high inflation. On the other hand, the blue line in Chart 2(c) shows that when import prices rise at a slower-than-average rate, the marginal effect does not differ significantly across quantiles, suggesting that the effect on

[18] Heise, Karahan, and Şahin (2021) show, both theoretically and empirically, that rising import penetration and increased market concentration have weakened the pass-through from wages to prices. The paper points out that in the United States, rising import penetration and increased market concentration have occurred at the same time, and that the increase in imports from China and other low-wage countries have forced domestic firms with low competitiveness to exit the market and resulted in an increase in U.S. domestic market concentration. Against this background, the paper presents a mechanism whereby a rise in domestic wages is less likely to be passed on to selling prices because this would mean a reduction in competitiveness relative to foreign firms that do not face an increase in wages.

inflation risks is also small. These results are also consistent with the asymmetry in the pass-through from exchange rates to prices during phases of exchange rate appreciation and depreciation noted by Delatte and López-Villavicencio (2012).[19]

Chart 2(d) suggests that while the marginal effect of the persistence of credit overheating at lower quantiles appears to have a downward effect on inflation risks, this effect is not statistically significant. Moreover, at the higher quantiles, there is no statistically significant relationship between the build-up of financial imbalances and inflation risks. A priori, we expected that since during phases of lower inflation nominal interest rates to also tend to be lower, prolonged financial imbalances would have a strong effect on downside risks to inflation because of the limited room for a policy response through traditional monetary policy in the event of a crisis. However, our results suggest that at least in the short term no such effect is observed. Meanwhile, López-Salido and Loria (2020) and Banerjee et al. (2020) report that financial stress indicators (credit spreads, volatility in equity returns) have a statistically significant effect on inflation risks at the lower quantiles. The reason for the different results may be that these studies use financial market prices that immediately reflect current and future information on the business cycle, so that they find a short-term impact on inflation risks; on the other hand, the financial imbalances measured by the persistence of credit overheating in this study tend to accumulate gradually over time, so that they may have a more medium-term impact on inflation risks. This issue is examined in more detail in the following section by estimating the term structure of the effect of the persistence of credit overheating on inflation risks.

Finally, we examine the marginal effects of the control variables. The coefficients on the lag of the inflation rate are larger for the higher quantiles (Chart 2(e)), which is consistent with the explanation that, as the menu cost model suggests, the frequency of price adjustments for individual items is higher during phases when the inflation rate is higher, leading to higher inflation at the macro-level.[20] On the other hand, with regard to the effect of the output gap, no significant differences across the quantiles are observed

[19] Delatte and López-Villavicencio (2012) argue that since during a phase of exchange rate depreciation import costs increase, there is an incentive to maintain markups by passing on cost increases to prices, while during a phase of exchange rate appreciation, import costs decrease, so there is an incentive to not pass this on to prices and increase markups.

[20] The fact that due to data constraints inflation expectations are not used as an explanatory variable may also have affected the magnitude of the effect at the higher quantiles. That is, since inflation expectations are thought to be influenced by the actual inflation rate, it is possible that some of the impact that would otherwise be explained by changes in inflation expectations is identified by this variable, changes in the actual inflation rate.

(Chart 2(f)).

4.2 The term structure of the effect of factors affecting inflation risks

So far, we have examined the marginal effect of each of the explanatory variables on one-year ahead inflation, i.e., the short term. However, it is also important to assess the persistence of inflation risks from a medium-term perspective, since it may take time for the real variables included among the explanatory variables to affect inflation risks, which are expressed in nominal terms. Therefore, in this section we combine the local projections approach by Jordà (2005) with panel quantile regression to estimate the effect of each explanatory variable on future inflation for different projection horizons from one to 12 quarters ahead. This is similar to the approach and methodology used by Adrian et al. (2021) and Aikman et al. (2019) in estimating the term structure of GDP growth-at-risk.

Chart 3 compares the term structures of the marginal effect of each explanatory variable at the 10th, 50th, and 90th percentile points (which will be referred to as the lower, medium, and upper quantile, respectively, in this section), with the marginal effect shown on the vertical axis and the projection horizon depicted on the horizontal axis. Chart 3(a) indicates that the marginal effect of real government spending on inflation risks for all quantiles appears to be persistent over a medium-term period from four quarters ahead onward. Moreover, for the upper quantile, the marginal effect increases with the forecast horizon for a period of up to eight quarters. This finding suggests that it takes time for real variables to affect inflation risks, which are a nominal value.

Next, for the upper quantile, the marginal effect of unit labor costs increases gradually over the medium term from the fourth quarter onward, as shown in Chart 3(b). This suggests that during periods of higher inflation the pass-through from labor costs to prices increases over time. In other words, in a phase of higher inflation, an increase in labor costs such as nominal wages raises the upside risks to inflation, and second-round spillover effects may be at work in which such higher inflation risks push up labor costs.

Chart 3(c) indicates that, for the upper quantile, the marginal effect of above-average increases in import prices is large in the short term up to about four quarters ahead; however, the effect does not persist in the medium term and is no longer statistically significant beyond that point. For the lower quantile, there is a slight effect in the short term but no statistically significant effect in the medium term. These estimates suggest that even during periods of higher inflation, the effect of larger increases in import prices on the upside risks to inflation is only temporary (short-term).

Chart 3(d) shows that the marginal effect of the persistence of credit overheating significantly raises downside inflation risks in the medium term, although the effect at the lower quantile is not statistically significant in the short term. On the other hand, for the medium and upper quantiles, the coefficients are negative in the medium term, but the effect is not statistically significant. This term structure suggests that while inflation risks do not necessarily materialize during the early stage of a build-up of financial imbalances, such imbalances may increase the downside risks to inflation in the medium term as financial imbalances begin to unwind through financial crises.

Finally, Chart 3(e) indicates that the marginal effect of the lag of the inflation rate for the lower and medium quantiles wanes as the forecast horizon increases, while for the upper quantile the effect persists in the medium term and onward. This suggests that medium-term inflation risks may also remain high when inflation is high. However, since we do not use inflation expectations as an explanatory variable in our analysis, it should be kept in mind that the estimates may be biased due to the omission of confounding variables. That is, the estimates of the marginal effect of the lag of the inflation rate at the upper quantile may be biased upward as a result of higher inflation expectations due to higher past realized values of the inflation rate.

4.3 Cross-country comparison of inflation risks

Next, using the predictive inflation distribution obtained by fitting a skewed *t*-distribution to the quantile function estimated by the panel quantile regression, we derive a measure of inflation risks. Specifically, we use the inflation rate at the 90th percentile of the predictive inflation distribution, defined as IaR_{90}, and the probability that the inflation rate exceeds a certain threshold as an indicator of upside risks and, conversely, the inflation rate at the 10th percentile of the predictive inflation distribution, IaR_{10}, and the probability that the inflation rate falls below a certain threshold as an indicator of downside risks.

Chart 4 shows the one-year ahead conditional predictive inflation distributions for the United States, Germany, and the United Kingdom. We find that for all three countries the shape of the entire predictive distribution shifted substantially to the right around the time of the oil crises in the 1970s. On the other hand, as shown in Chart 5, in the case of the two-years ahead conditional distribution, the distribution overall did not shift to the right in the 1970s and became more skewed to the right, suggesting different dynamics from the one-year ahead conditional distribution. This skew to the right of the medium-term predictive distribution in the 1970s can to some extent be explained by the differences in the marginal effect of import prices at each quantile as well as differences in its term structure. First, since the effect of higher import prices on the upside risks to inflation is only short-term, the thickness of the right tail of the predictive inflation distribution declines when the forecast horizon extends to the medium term. Second, in terms of the difference in the marginal effect of import prices at each quantile, we find that the effect at the middle and lower quantiles is smaller than that at the upper quantile, and that the term structure of the effect at the middle and lower quantiles is flatter than that at the upper quantile, as shown in Chart 3(c). This may be responsible for the difference between the shape of the probability density at higher quantiles and that at the middle and lower quantiles, and together with the short-run effect of higher import prices, may have skewed the predictive distribution. Meanwhile, the medium-term predictive distribution for the 1970s shows a small but non-zero probability at the right tail, suggesting that upside risks to inflation remain. This point will be explained later when we look at Charts 7 and 8, which also take the effects of wages and government spending into account.

We define the tail risk of these predictive inflation distributions as IaR_{90} and IaR_{10} and show developments in these in Chart 6 (left side: one year ahead; right side: two years ahead). During the "Great Inflation" (from the late 1960s to early 1980s), the United States, Germany, and the United Kingdom all experienced an increase in inflation risks, especially in upside risks to inflation (IaR_{90}). Subsequently, during the "Great Moderation" (from the late 1980s onward), both IaR_{90} and IaR_{10} fell, and during some periods, IaR_{10} was negative, indicating downside risks to inflation. Subsequently, in the wake of the pandemic, inflation risks in the United States and the United Kingdom have increased not only in the short term but also in the medium term (i.e., IaR_{90} in the case of two-years ahead forecasts has increased).

Next, taking advantage of the quantile regression model, we examine the drivers affecting the dynamics of upside inflation risks (Charts 7 and 8). Focusing first on the United States, during the "Great Inflation," the rise in import prices (red) had a significant short-term impact, while the fact that inflation remained high (as represented by the lag of the inflation rate, shown in blue) also contributed to the increase in inflation risks. Turning to the results for the medium term, while the lag of the inflation rate continues to make a substantial contribution, the contribution of rising import prices is now only marginal, while the rise in unit labor costs (green) now makes a large contribution. Moreover, examining the situation since the outbreak of the pandemic shows that import prices in the short term and unit labor costs in the medium term have contributed to the rise in upside risks to inflation, indicating that although the magnitude of the contributions differs, the same mechanisms as observed during the "Great Inflation" are at work. Meanwhile, real government spending is making a relatively large contribution to the upside risks to inflation in the United Kingdom, but in our estimation period it made almost no contribution in the case of the United States and Germany.

Next, we examine the drivers affecting inflation risk dynamics in Germany and the United Kingdom, focusing on differences with the United States. In Germany, the increase in upside inflation risks during the "Great Inflation" was smaller than in the United States. In addition to the fact that the increase in the inflation rate was relatively small (effect of the lag of the inflation rate: blue), the fact that under these circumstances wage hikes in wage negotiations between employers and labor union remained modest (effect of unit labor costs: green) is another factor that kept upside risks to inflation in check. This finding is consistent with Issing's (2005) argument that Germany managed to avoid second-round effects. In contrast, upside risks to inflation in the United Kingdom during the "Great Inflation" were significantly higher than in the United States, due to the persistently high inflation rate and sustained wage increases through negotiations between employers and labor union.

Furthermore, Chart 9 (left side: one-year ahead; right side: two-years ahead) shows the probability of a deviation of 2 percentage points or more from the current inflation target of 2 percent for each country in the short and medium term (i.e., the probability that inflation falls below 0 percent or rises above 4 percent). In the case of the United States, during the "Great Inflation," the upside risks to inflation remained high in both the short and medium term, partly because inflation remained high for a long period of time. These upside risks gradually declined, partly due to the monetary policies implemented by Federal Reserve Chairman Paul Volcker during the early 1980s and remained low during the "Great Moderation." Before the global financial crisis, there was a phase of renewed upside risks to inflation, mainly in the short term, due to rising commodity prices, but after the global financial crisis, we can observe a turnaround and an increase in downside risks. In the wake of the pandemic, upside risks to inflation – both short and medium term – have increased again and are at the highest level since inflation targets were set. These results are in line with the findings of López-Salido and Loria (2020), who argue that the probability of a decline in inflation risks increased following the global financial crisis, although some of their explanatory variables are different from ours.

We also examine the probability of a deviation from the inflation target for Germany and the United Kingdom. Although inflation risk dynamics in the United Kingdom have been generally similar to those in the United States, if we focus on inflation risks in the wake of the pandemic, these have already reached a level exceeding that before the global financial crisis, indicating that there has been a marked increase in upward risks. On the other hand, in Germany, there have been several instances since the introduction of the euro in 1999 when both short- and medium-term downside risks increased, suggesting that the situation differs from that of the United States and the United Kingdom. Meanwhile, although downside risks have decreased substantially in the wake of the pandemic, the increase in upside risks appears to be relatively limited.

4.4 The changing role of labor costs and real government spending in inflation risks

Finally, we conduct further analyses of the role of labor costs and real government spending by extending the model with additional explanatory variables. We start by examining the extent to which the marginal effect of unit labor costs on inflation risks depends on a country's trade dependence. Next, we examine how the marginal effect of real government spending on inflation risks differs depending on the level of outstanding government debt.

With regard to the role of trade dependence, we use a dummy variable ($I_{i,t}^{trade}$) that takes 1 when a country's import-to-GDP ratio exceeds its long-term historical average as a proxy variable for trade dependence, and distinguish between the case when the ratio is above and below the average by including the interaction term between the dummy and unit labor costs ($\Delta ULC_{i,t} \cdot I_{i,t}^{trade}$).

The estimation results are presented in Tables 3 and 4 and show that the coefficients are significant at each quantile for both one-year and two-years ahead forecasts when the import ratio is below the average, while the coefficients are not significant when the import ratio is above the average. This implies that even in a phase of higher inflation, labor costs are less likely to have an effect on upside risks to inflation when a country's import penetration is high due to globalization. This finding is consistent with the empirical results of Heise, Karahan, and Şahin (2021)[21] and is also an important aspect

[21] The mechanism presented by Heise, Karahan and Şahin (2021) assumes a wage shock that affects only domestic firms, an aspect that differs from the global supply chain bottlenecks that have emerged

when assessing the current increase in inflation risks. That is, the effect of labor costs on upside risks to inflation in the wake of the pandemic may be relatively small partly because of advanced economies' high degree of import penetration as a result of globalization.

Next, we examine the role of real government spending in inflation risk. We construct a dummy ($I_{i,t}^{GovtDebt}$) that takes 1 if the ratio of government debt to GDP exceeds the average of the entire sample, and distinguish between the case when the ratio is above and below the average by including the interaction term between the dummy and real government spending ($\Delta GovtSpend_{i,t} \cdot I_{i,t}^{GovtDebt}$). Moreover, with regard to the threshold for government debt outstanding, in addition to the case where the dummy takes 1 if it is above the average, we also construct a dummy that takes 1 when it exceeds more than one standard deviation from the average ($I_{i,t}^{GovtDebt\_1\sigma}$).

The estimation results shown in Tables 3 and 4 indicate that when the average of outstanding government debt is used as the threshold, there is no difference in the significance and magnitude of the coefficients on real government spending at the lower and medium quantiles, regardless of the forecast horizon (one or two years ahead). For the upper quantile, the coefficient is significant only during phases when government debt outstanding is above average, while there is no difference in the size of the coefficient from the lower and medium quantiles. On the other hand, when the criterion is whether real government spending deviates by more than one standard deviation from the mean of the entire sample, the coefficient on real government spending is significant when government debt is above the threshold, regardless of the forecast horizon or quantile, and in the case of both one- and two-year forecasts ahead, the coefficient for the upper quantile is larger than those for the lower and medium quantiles. These results suggest that increasing government spending during a phase in which the level of outstanding government debt is high has a much greater effect on the upside risks to inflation than during phases in which the level of outstanding government debt is below the threshold.[22] One possible explanation for this is that further increases in government spending when

---

in the wake of the pandemic. When labor costs rise, including in emerging economies, it is possible that domestic firms are more likely to pass on labor costs to product prices, even when import dependence is high, because passing on labor costs to product prices does not necessarily lead to a decline in global competitiveness.

[22] Reinhart and Rogoff (2010) report that for emerging economies, inflation tends to be higher when government debt levels are high (above 90 percent of GDP), while no such tendency is observed for advanced economies. This is consistent with the fact that the effect of government spending on the future inflation does not depend on the level of outstanding debt at the medium quantile in our estimation results.

outstanding government debt is high may lead to concerns that fiscal balance cannot be achieved through future tax increases alone and that there is a risk that real government debt has to be brought down by inflation (Davig and Leeper, 2011; Beck-Friis and Willems, 2017).

In this context, as pointed out by Blanchard (2020), it may be necessary to keep in mind the possibility that additional large-scale fiscal spending could increase the upside risks to inflation, even in advanced economies, in the current situation where government debt has risen in response to the pandemic. That said, looking at the current situation, it should also be taken into account that in the United States for example, at the same time that large-scale fiscal policies are being implemented, there are also discussions about future revenues such as tax rises, and that fiscal policy is conducted with an eye on the fiscal balance.

5 Conclusion

In this paper, we used panel quantile regression to estimate the conditional predictive distribution of inflation and examined both upside and downside risks to inflation. Moreover, we also analyzed the term structure of the effect of factors affecting these risks. In light of the increase in inflation in the United States and many European countries in the wake of the pandemic, we explicitly incorporated into our model factors capturing upward risks to inflation that have not been fully examined in previous studies, and we find that real government spending and unit labor costs, especially at the higher quantiles, have an effect on inflation risks. In addition, we found that while the effect of import prices on inflation risks is only short-term, the effect of unit labor costs and real government spending persists over the medium term, indicating that the different factors affecting inflation risks have different term structures in terms of their effect on inflation risks.

The estimation results of inflation risks in the United States and some European countries showed that factors similar to those during the "Great Inflation" have increased inflation risks in the wake of the pandemic, although the extent to which they contribute to the increase in inflation risks differs across factors. It is important to note, however, that risks like those that emerged in the past may be less likely to manifest today due to changes in the structure of the economy, including globalization, and a better understanding of monetary and economic policies.

Finally, one direction for future research is to examine inflation risks by sector. As a result of increased international competition in goods markets through globalization, goods prices in developed countries have become less likely to rise, while service prices have seen domestic demand-driven fluctuations. Therefore, it is possible that the drivers of inflation risk dynamics examined in this paper also differ for the goods and services markets, and examining inflation risk dynamics by sector should make it possible to examine the impact of globalization in more detail.

References

Adrian, T., Boyarchenko, N., and Giannone, D. (2019). "Vulnerable Growth," *American Economic Review*, 109(4), 1263-1289.

Adrian, T., Grinberg, F., Liang, N., Malik, S., and Yu, J. (2021). "The Term Structure of Growth-at-Risk," forthcoming in *American Economic Journal: Macroeconomics*.

Aikman, D., Bridges, J., Hacioglu Hoke, S., O'Neill, C., and Raja, A. (2019). "Credit, Capital and Crises: a GDP-at-Risk Approach," Bank of England Staff Working Paper No. 824.

Amisano, G. and Giacomini, R. (2007). "Comparing Density Forecasts via Weighted Likelihood Ratio Tests," *Journal of Business & Economic Statistics*, 25(2), 177-190.

Azzalini, A. and Capitanio, A. (2003). "Distributions Generated by Perturbation of Symmetry with Emphasis on a Multivariate Skew t-Distribution," *Journal of the Royal Statistical Society*, Series B, 65, 367-389.

Azzalini, A. (2021). The Skew-Normal and Related Distributions Such as the Skew-t and the SUN. "sn" package for R.

Banerjee, R., Contreras, J., Mehrotra, A., and Zampolli, F. (2020). "Inflation at Risk in Advanced and Emerging Market Economies," BIS Working Papers No. 833.

Basel Committee on Banking Supervision (2010). "Guidance for National Authorities Operating the Countercyclical Capital Buffer," Bank for International Settlements.

Beck-Friis, P. and Willems, T. (2017). "Dissecting Fiscal Multipliers under the Fiscal Theory of the Price Level," *European Economic Review*, 95, 62-83

Beechey, M. J., Johannsen, B. K., and Levin, A. T. (2011). "Are Long-run Inflation Expectations Anchored More Firmly in the Euro Area than in the United States?" *American Economic Journal: Macroeconomics*, 3(2).

Bernanke, B., Gertler, M. and Gilchrist, S. (1999). "The Financial Accelerator in a Quantitative Business Cycle Framework," in J. Taylor and M. Woodford (eds), *Handbook of Macroeconomics*, vol.1, North Holland, Amsterdam.

Besstremyannaya, G., and Golovan, S. (2019). "Reconsideration of a Simple Approach to Quantile Regression for Panel Data," *The Econometrics Journal*, 22, pp.292-308.

Blanchard, O. (2020). "Is There Deflation or Inflation in Our Future?" VOXEU, April 24th.

Bobeica, E., Ciccarelli, M., and Vansteenkiste, I. (2019). "The Changing Link between Labor Cost and Price Inflation in the United States," ECB Working Paper No. 2583.

Bordo, M. D., and Eichengreen, B. (2014). "Bretton Woods and the Great Inflation," *The Great Inflation: The Rebirth of Modern Central Banking*, edited by Bordo, M. D., and Orphanides, A., p. 449-489, The University of Chicago Press.

Coibion, O. and Gorodnichenko, Y. (2011). "Monetary Policy, Trend Inflation, and the Great Moderation: An Alternative Interpretation," *American Economic Journal*, 101(1), 341-370.

Davig, T. and Leeper, E. M. (2011). "Monetary–Fiscal Policy Interactions and Fiscal Stimulus," *European Economic Review*, 55(2), 211-227

Davis, J. S., (2014). "Inflation Targeting and the Anchoring of Inflation Expectations: Cross-country Evidence from Consensus Forecasts," Federal Reserve Bank of Dallas Working Paper No. 174.

Delatte, A. L. and López-Villavicencio, A. (2012). "Asymmetric Exchange Rate Pass-Through: Evidence from Major Countries," *Journal of Macroeconomics*, 34(3), 833-844.

Devereux, M. B. and Yetman, J. (2010). "Price Adjustment and Exchange Rate Pass-Through," *Journal of International Money and Finance*, 29(1), 181-200.

Eggertsson, G. B., Mehrotra, N. R. and Robbins, J. A. (2019). "A Model of Secular Stagnation: Theory and Quantitative Evaluation," *American Economic Journal: Macroeconomics*, 11(1), 1-48.

Ehrmann, M. (2021). "Point Targets, Tolerance Bands, or Target Ranges? Inflation Target Types and the Anchoring of Inflation Expectations," CESifo Working Paper No. 9034.

Engel, F., R. (1983). "Estimates of the Variance of U.S. Inflation Based upon the ARCH Model," *Journal of Money, Credit and Banking*, 15(3), 286-301.

Fleckenstein, M., Longstaff, F. A. and Lustig, H., (2017). "Deflation Risk," *The Review of Financial Studies*, 30(8), 2719-2760.

Gagnon, J.E. and Ihrig, J. (2004). "Monetary Policy and Exchange Rate Pass-through," *International Journal of Finance and Economics*, 9(4), 315-338.

Grier, K. B. and Perry, M. J. (1998). "On Inflation and Inflation Uncertainty in the G7 Countries," *Journal of International Money and Finance*, 17 671-689.

Gürkaynak, R. S., Levin, A., and Swanson, E. (2010). "Does Inflation Targeting Anchor Long-run Inflation Expectations? Evidence from the U.S., UK, and Sweden." *Journal of the European Economic Association*, 8(6), 1208-1242.

Hamilton, J. D. (2018). "Why You Should Never Use the Hodrick-Prescott Filter," *The Review of Economics and Statistics*, 100 (5), 831–843.

Hammond, G. (2012). "State of the Art of Inflation Targeting," Handbook No. 29, Center for Central Banking Studies, Bank of England.

Heise, S., Karahan, F., and Şahin, A. (2021). "The Missing Inflation Puzzle: The Role of the Wage-Price Pass-Through," forthcoming in *Journal of Money, Credit and Banking*.

Hördahl, P., and Tristani, O. (2014). "Inflation Risk Premia in the Euro Area and the United States." *International Journal of Central Banking*, 10(3), 1-47.

International Monetary Fund, (2022). *World Economic Outlook*, January.

International Monetary Fund, (2020). *World Economic Outlook*, October.

Ireland, P., (2007). "Changes in the Federal Reserve's Inflation Target: Causes and Consequences," *Journal of Money, Credit and Banking*, 39(8), 1851-1882.

Issing, O. (2005). "Why Did the Great Inflation Not Happen in Germany?" *Review* 87(2) 329-336, Federal Reserve Bank of St. Louis.

Ito, Y., Kitamura, T., Nakamura, K., and Nakazawa, T. (2014). "New Financial Activity Indexes: Early Warning System for Financial Imbalances in Japan, Bank of Japan Working Paper Series No. 14-E-7.

Jordà, Ò. (2005). "Estimation and Inference of Impulse Responses by Local Projections," *American Economic Review*, 95(1), 161-182.

Jordà, Ò., Francisco, S., Kornejew, M., Schularick, M., Taylor, A. M., and Jordà, O. (2020). "Zombies at Large? Corporate Debt Overhang and the Macroeconomy," NBER Working Paper No. 28197.

Kitsul, Y., and Wright, J. H. (2013). "The Economics of Options-implied Inflation Probability Density Functions," *Journal of Financial Economics*, 110(3), 696-711.

Kiyotaki, N. and Moore, J. (1997). "Credit Cycles," *Journal of Political Economy*, Vol. 105, No. 2 (April 1997), 211-248.

Koenker, R. (2004). "Quantile Regression for Longitudinal Data," *Journal of Multivariate Analysis*, 91, 74-89.

Korobilis, D., Landau, B., Musso, A., and Phella, A. (2021). "The Time-varying Evolution of Inflation Risks," ECB Working Paper No. 2600.

Kupfer, A. (2018). "Estimating Inflation Risk Premia Using Inflation-linked Bonds: A Review," *Journal of Economic Surveys*, 32(5), 1326-1354.

Leduc, S., Sill, K. and Stark, T. (2007). "Self-fulfilling Expectations and the Inflation of the 1970s: Evidence from the Livingston Survey," *Journal of Monetary Economics*, 54(2) 433-459.

Leigh, D., (2008). "Estimating the Federal Reserve's Implicit Inflation Target: A State Space Approach," *Journal of Economic Dynamics and Control*, 32(6), 2013-2020.

Linnemann, L., and Winkler, R. (2016). "Estimating Nonlinear Effects of Fiscal Policy Using Quantile Regression Methods," *Oxford Economic Papers*, 68(4), 1120-1145.

López-Salido, D., and Loria, F. (2020). "Inflation at Risk," Finance and Economics Discussion 2020-013, Board of Governors of the Federal Reserve System.

Loria, F., Matthes, C., and Zhang, D. (2019). "Assessing Macroeconomic Tail Risk," Finance and Economics Discussion 2019-026, Board of Governors of the Federal Reserve System.

Manzan, S., and Zerom, D. (2013). "Are Macroeconomic Variables Useful for Forecasting the Distribution of U.S. Inflation?" *International Journal of Forecasting*, 29(3), 469-478.

Mehra, Y. P. (2000). "Wage-price Dynamics: Are They Consistent with Cost Push?" *Economic Quarterly*, 86(3), 27-43.

Meltzer, A. H. (2005). "Origins of the Great Inflation," *Federal Reserve Bank of St. Louis Review*, 87(2 II).

Mishkin, F. S. (1999). "International Experiences with Different Monetary Policy Regimes," *Journal of Monetary Economics*, 43(3), 579-605.

Orphanides, A., and Williams, J. C. (2005). "The Decline of Activist Stabilization Policy: Natural Rate Misperceptions, Learning and Expectations." *Journal of Economic Dynamics and Control*, 29:1927–50.

Peneva, E. V., and Rudd, J. B. (2017). "The Passthrough of Labor Costs to Price Inflation," *Journal of Money, Credit and Banking*, 49(8), 1777-1802.

Reinhart, C. and Rogoff, K. (2010). "Growth in a Time of Debt," *American Economic Review: Papers & Proceedings*, 100(2), 573-578.

Stock, J. H., and Watson, M. W. (2007). "Why Has U.S. Inflation Become Harder to Forecast?" *Journal of Money, Credit and Banking*, 39(7), 3-33.

Summers. L. H. (2021). "The Inflation Risk is Real," *The Washington Post*, May 24th.

Appendix 1: Data Description

This appendix provides details of the data used in the estimation. Starting with the dependent variable, the inflation rate, we use the year-on-year rate of change in the consumer price index (all items) published by the OECD.

Next, we outline the explanatory variables in more detail. For real government spending, we use the sum of real government consumption and real government investment. For the United States, Germany, Japan, and the United Kingdom, we use quarterly data from the GDP statistics of each country. For the other countries, nominal government spending on an annual basis published by the OECD is converted to quarterly figures through linear interpolation and then deflated using the GDP deflator. U.S. government spending does not include social security benefits such as Medicare and Medicaid. Therefore, to bring U.S. government spending data in line with data for other countries where such items are included in government spending, we take data for Medicare and Medicaid published by the Centers for Medicare and Medicaid Services (on an annual basis converted to a quarterly basis through linear interpolation), deflate the data using the GDP deflator, and add it to government spending. Next, for unit labor costs we in principle use the values published by the OECD, but for periods when data are not available, we use the ratio of labor compensation to real GDP to link the data. For import prices, we use the import deflator calculated from nominal and real imports published by the OECD. For the persistence of credit overheating, we use the credit-to-GDP gap (total credit to nominal GDP) published by the Bank for International Settlements.

Finally, we explain our control variables in more detail. For the output gap, we use the deviation of real GDP from potential GDP as published by the Congressional Budget Office for the United States. For the other countries, following Banerjee et al. (2020), who use panel quantile regression to measure inflation risks, we estimate the output gap using Hamilton's (2018) methodology. Next, for periods during which a nominal anchor is in place, we use (1) the period during which the fixed exchange rate system under the Bretton Woods system was maintained, and (2) periods during which an inflation target was adopted.

For (1), the period is defined as the period up to 1971Q3, when the convertibility of the U.S. dollar to gold was terminated, and for (2), periods are defined as periods from when a central bank officially adopted an inflation target, with the dates taken from Ehrmann (2021) and Hammond (2012). Meanwhile, although the euro area and Switzerland have not officially adopted inflation targeting policies, we use the periods from when a numerical definition of price stability was introduced as periods in which a nominal anchor was in place.

All of the numerical data mentioned here were obtained from the database provided by Haver Analytics.

Appendix 2: Validity of the Approximation of the Quantile Function by a Skewed *t*-Distribution

In this appendix, we check for approximation errors in fitting the skewed *t*-distribution to the quantile function (empirical distribution) estimated using quantile regression. Appendix Chart A1.1 compares the cumulative density functions of the estimated quantile functions (blue lines with blue x's) and the fitted skewed *t*-distribution functions (red lines) for the United States, Germany, and the United Kingdom for one year ahead. Similarly, Appendix Chart A1.2 compares the cumulative density functions for two years ahead. The comparison of these cumulative density functions shows that the approximation errors between the estimated quantile functions and the skewed *t*-distributions are small, and that the analyses and interpretations of inflation risks using risk indicators derived from the fitted skewed *t*-distributions are reliable.

Table 1: Summary Statistics

<Full Observation Periods>

	Mean	Median	Std. dev.	10%ile	90%ile	No. of obs.
Inflation rate, yoy, %	3.84	2.54	4.04	0.28	9.33	1,967
Real government spending, yoy, %	2.39	2.22	3.16	-1.07	6.24	1,967
Unit labor cost, yoy, %	3.67	2.57	4.83	-0.75	9.54	1,967
Import price, yoy, %	3.12	1.86	9.03	-4.17	11.66	1,967
Persistence of credit overheating, [0, 1]	0.14	0.00	0.32	0.00	0.83	1,967
Output gap, %	0.03	0.40	3.08	-4.05	3.78	1,967

<Periods in Which a Nominal Anchor was in Place>

	Mean	Median	Std. dev.	10%ile	90%ile	No. of obs.
Inflation rate, yoy, %	1.88	1.77	1.48	0.10	3.68	901
Real government spending, yoy, %	2.25	2.04	3.38	-1.35	6.08	901
Unit labor cost, yoy, %	2.03	1.75	2.65	-0.87	5.15	901
Import price, yoy, %	1.08	1.09	4.39	-4.33	6.25	901
Persistence of credit overheating, [0, 1]	0.18	0.00	0.34	0.00	0.92	901
Output gap, %	0.60	1.12	3.06	-3.79	4.11	901

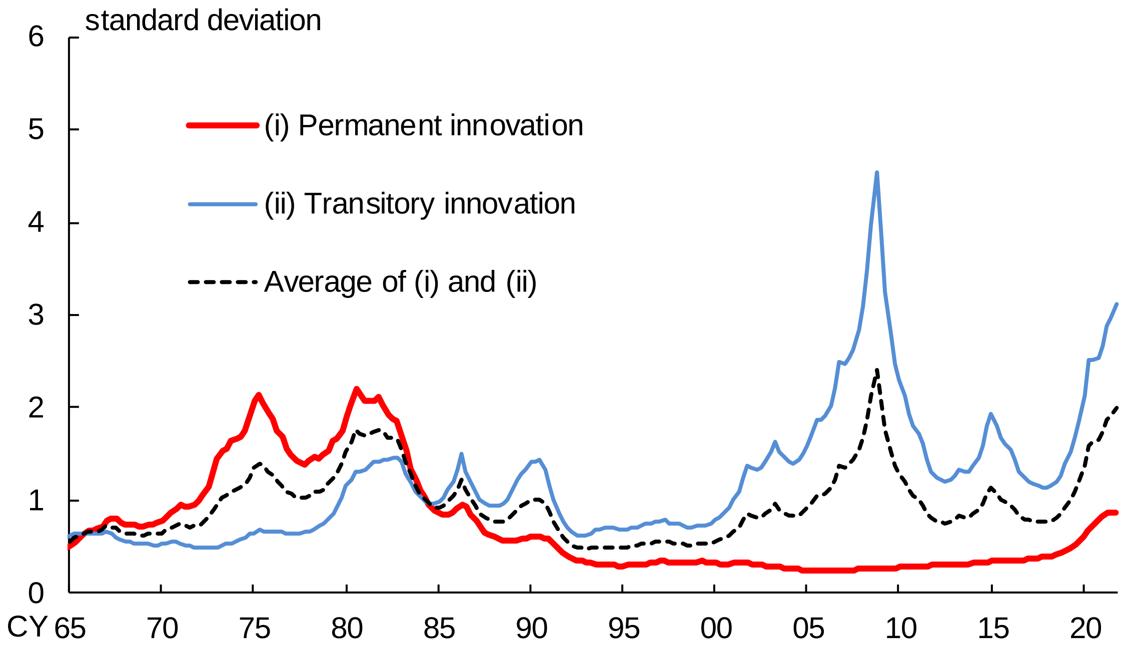
<Periods When No Anchor was in Place>

	Mean	Median	Std. dev.	10%ile	90%ile	No. of obs.
Inflation rate, yoy, %	5.49	4.28	4.73	0.75	12.08	1,066
Real government spending, yoy, %	2.50	2.34	2.96	-0.81	6.31	1,066
Unit labor cost, yoy, %	5.05	3.68	5.75	-0.56	11.47	1,066
Import price, yoy, %	4.84	2.77	11.31	-4.04	16.21	1,066
Persistence of credit overheating, [0, 1]	0.12	0.00	0.29	0.00	0.67	1,066
Output gap, %	-0.46	-0.24	3.03	-4.27	3.17	1,066

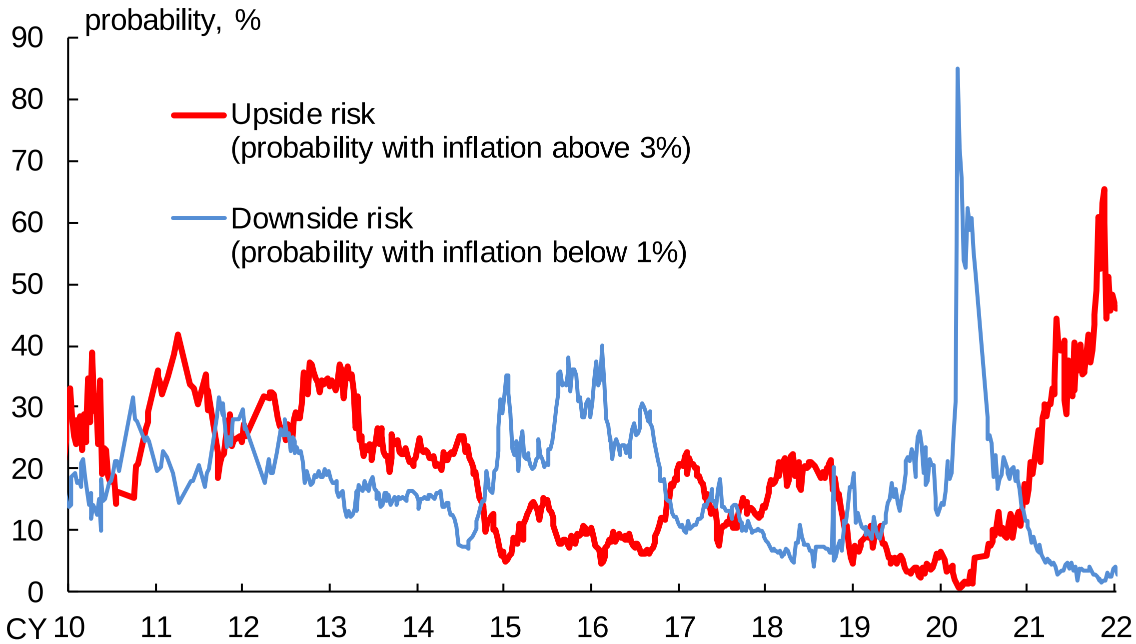
Source: Authors' calculation based on data from Haver.

Chart 1: U.S. Inflation Uncertainty

(a) Inflation Uncertainty from the Time-series Perspective



(b) Inflation Uncertainty from the Financial Engineering Perspective



Note: Figures in (a) show the estimated value using UC-SV model proposed by Stock and Watson (2007). Figures in (b) shows the value derived from the 5-year ahead inflation distribution estimated through the model proposed by Kitsul and Wright (2013).

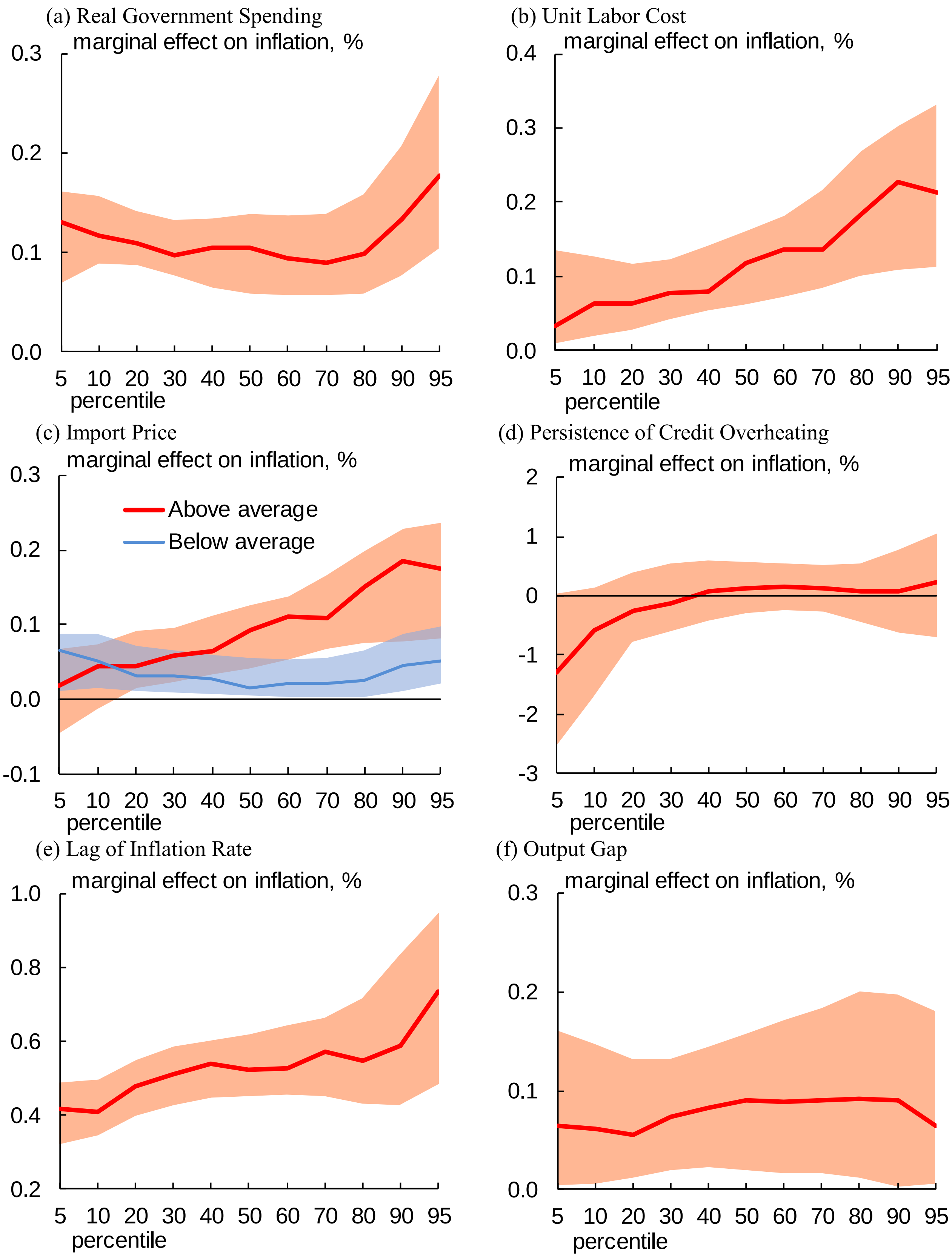
Sources: Fed Minneapolis; Authors' calculation based on data from Haver.

Table 2: Expected Coefficient Signs

	Short term			Medium term		
	Quantiles			Quantiles		
	Lower	Middle	Upper	Lower	Middle	Upper
Real government spending	±	±	±	+	+	+
Unit labor cost	+	+	+	+	+	+
Import price (including interaction term)	+	+	+	±	±	±
Persistence of credit overheating	-	±	±	-	-	-

Red	Positive sign expected
Blue	Negative sign expected
Yellow	No statistically significant sign expected, or either positive or negative

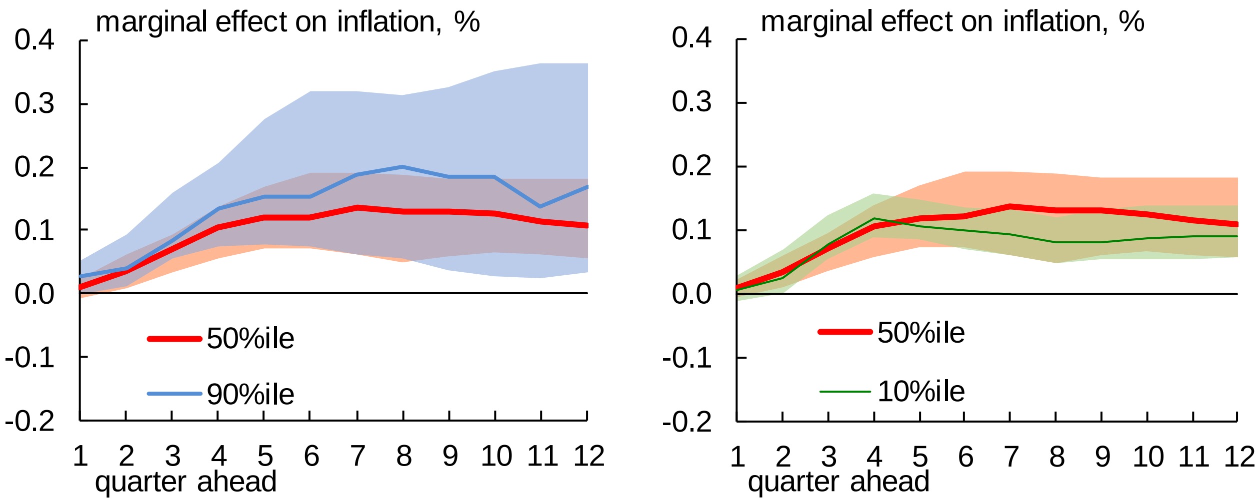
Chart 2: Marginal Effect of Each Risk Factor on One-year-ahead Inflation



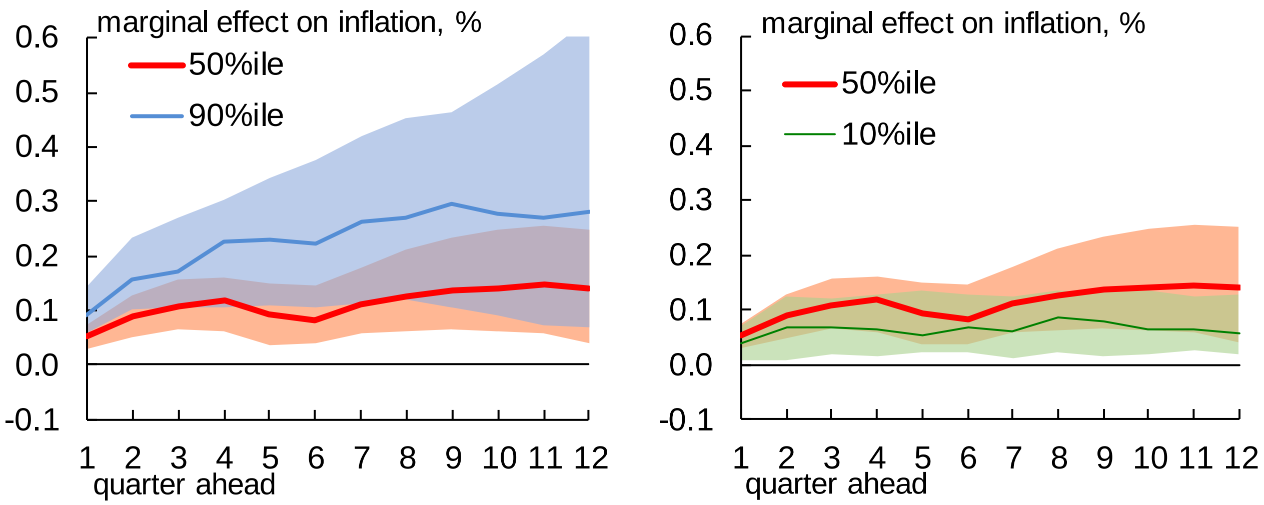
Note: The shaded areas show the 5 to 95 percent confidence interval obtained using the block bootstrap method.
Source: Authors' calculation based on data from Haver.

Chart 3: Term Structure of the Marginal Effect of Each Risk Factor (1)

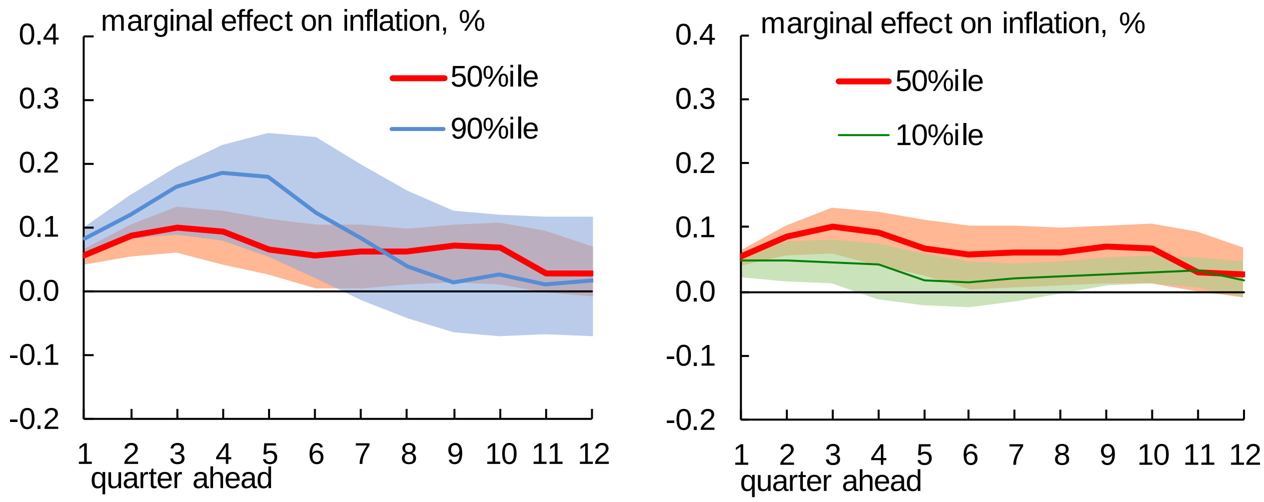
(a) Real Government Spending



(b) Unit Labor Cost



(c) Import Price (rate of increase exceeds the historical average)

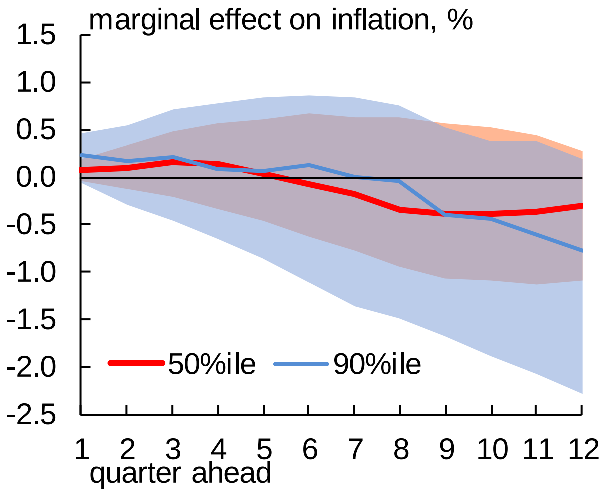


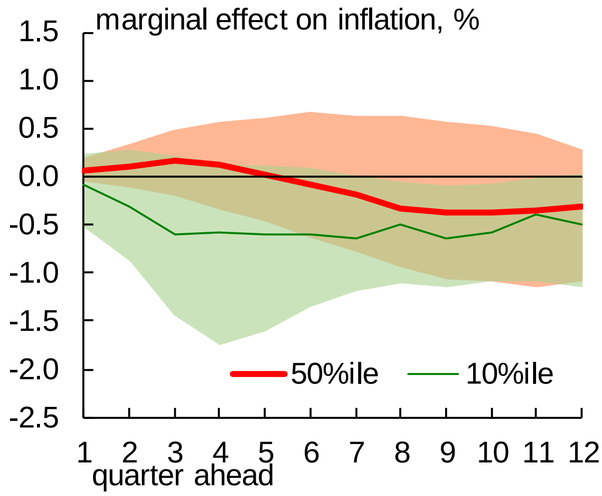
Note: The shaded areas show the 5 to 95 percent confidence interval obtained using the block bootstrap method.

Source: Authors' calculation based on data from Haver.

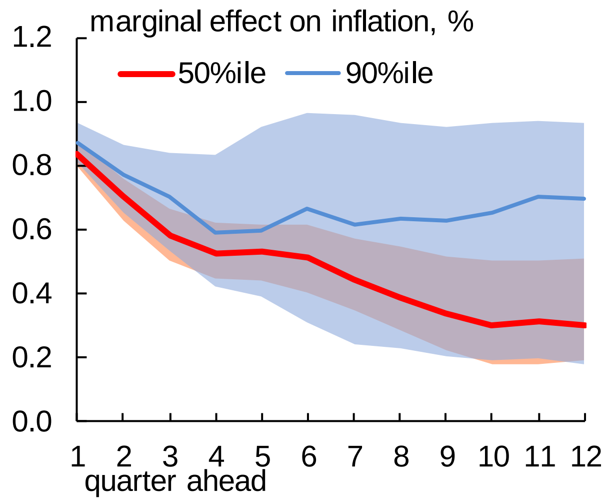
Chart 3: Term Structure of the Marginal Effect of Each Risk Factor (2)

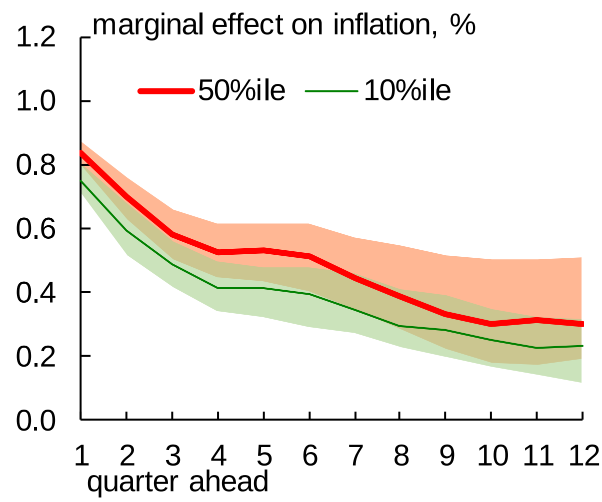
(d) Persistence of Credit Overheating



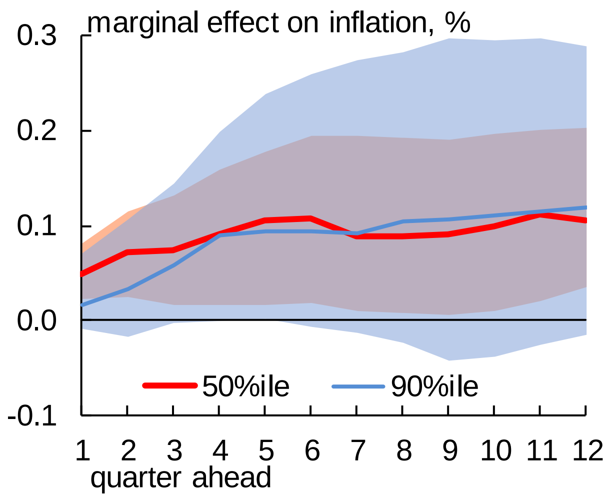


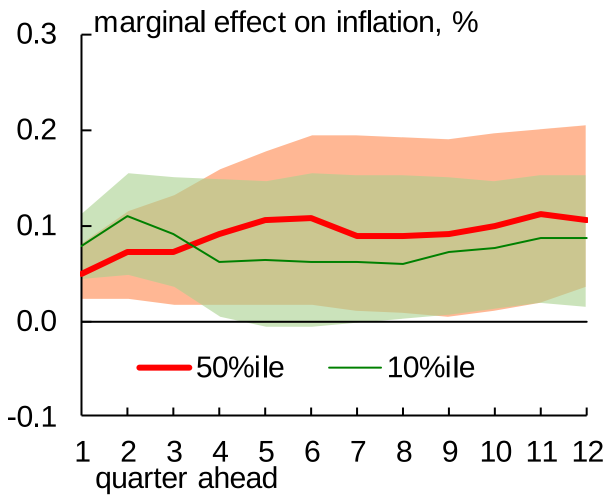
(e) Lag of Inflation Rate





(f) Output Gap

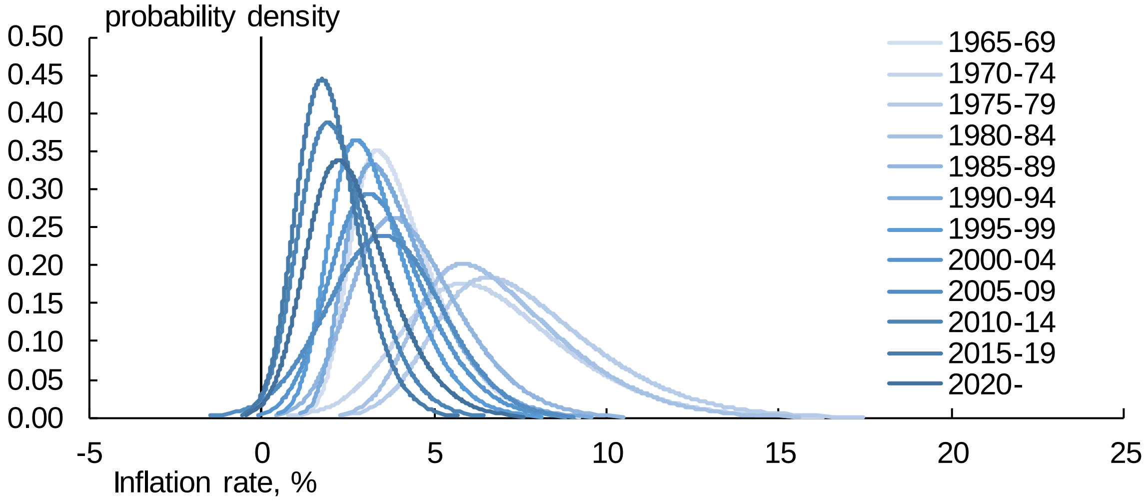




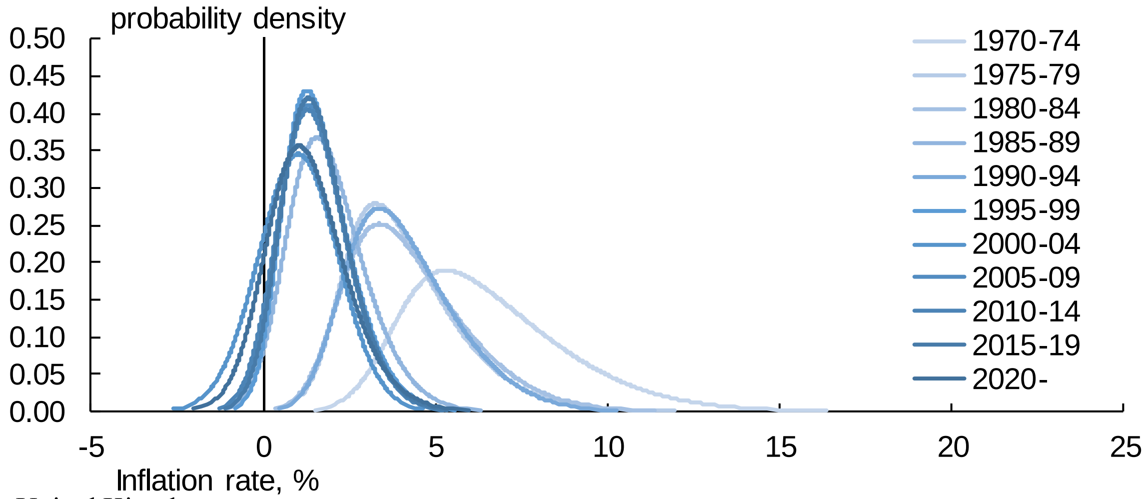
Note: The shaded areas show the 5 to 95 percent confidence interval obtained using the block bootstrap method.
Source: Authors' calculation based on data from Haver.

Chart 4: Dynamics of the One-year-ahead Predictive Inflation Distribution

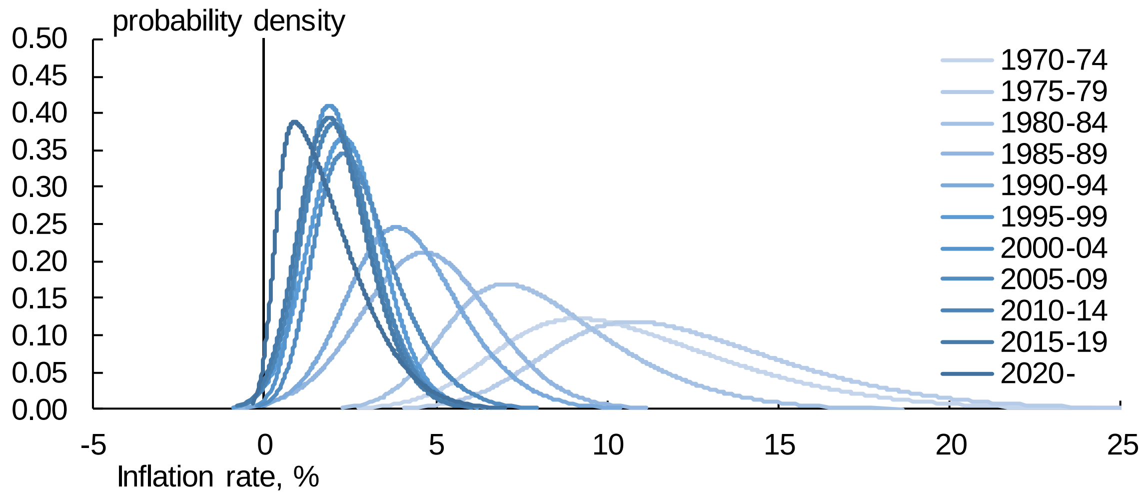
(a) the United States



(b) Germany



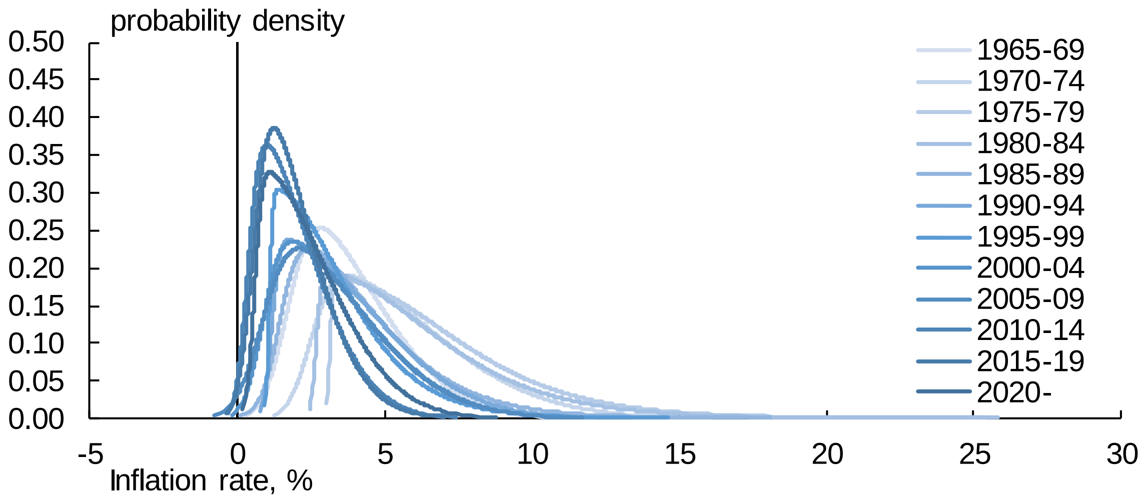
(c) the United Kingdom



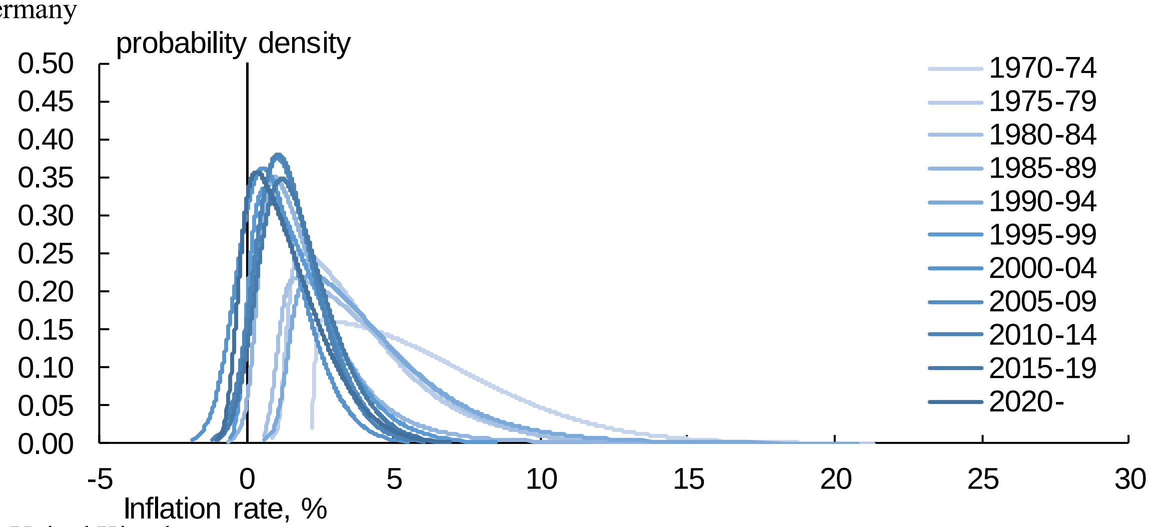
Source: Authors' calculation based on data from Haver.

Chart 5: Dynamics of the Two-year-ahead Predictive Inflation Distribution

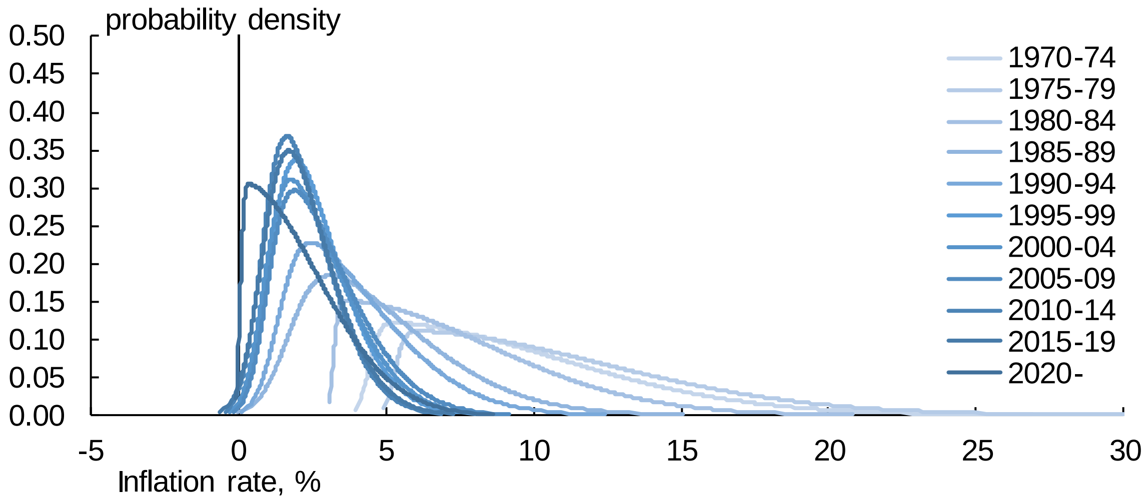
(a) the United States



(b) Germany



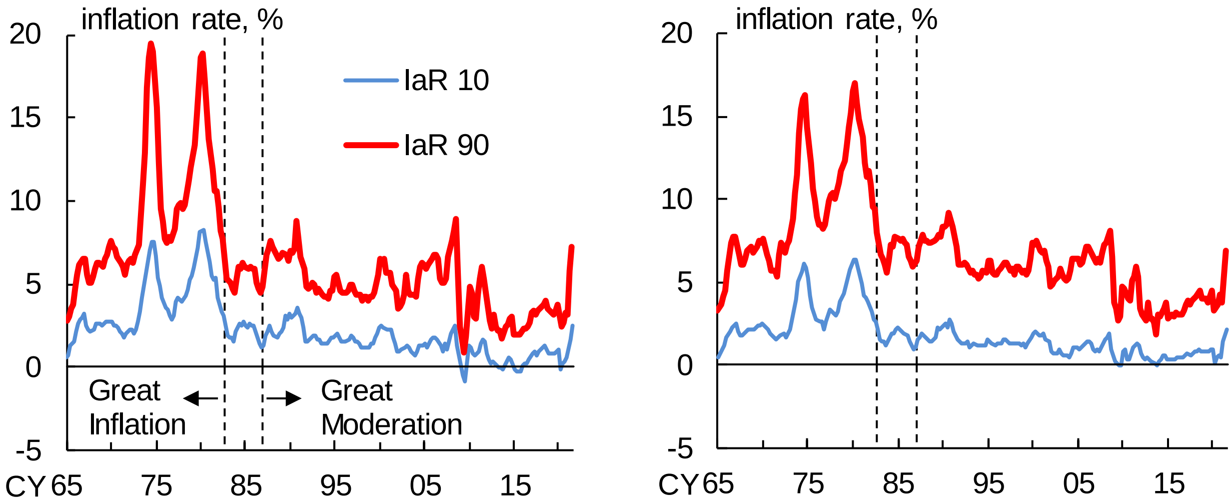
(c) the United Kingdom



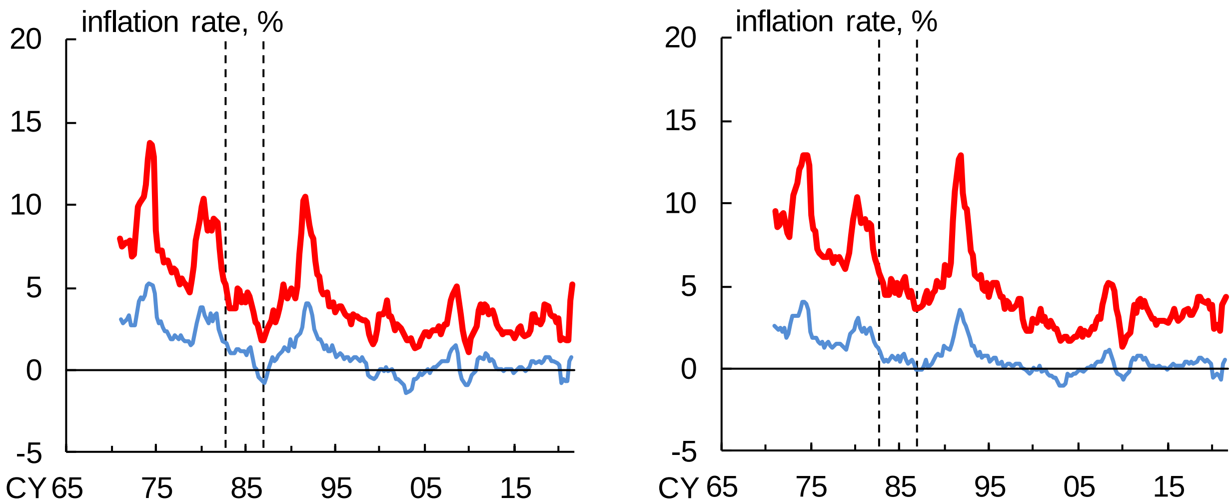
Source: Authors' calculation based on data from Haver.

Chart 6: Inflation at Risk (Upper and Lower 10%ile)

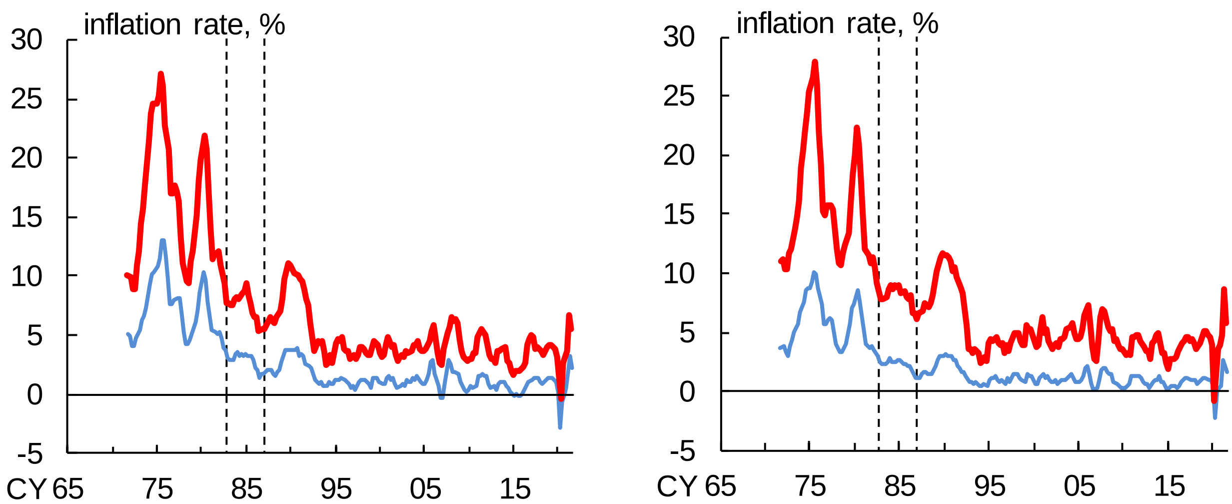
(a) the United States (LHS: 1-year ahead, RHS: 2-year ahead)



(b) Germany (LHS: 1-year ahead, RHS: 2-year ahead)



(c) the United Kingdom (LHS: 1-year ahead, RHS: 2-year ahead)

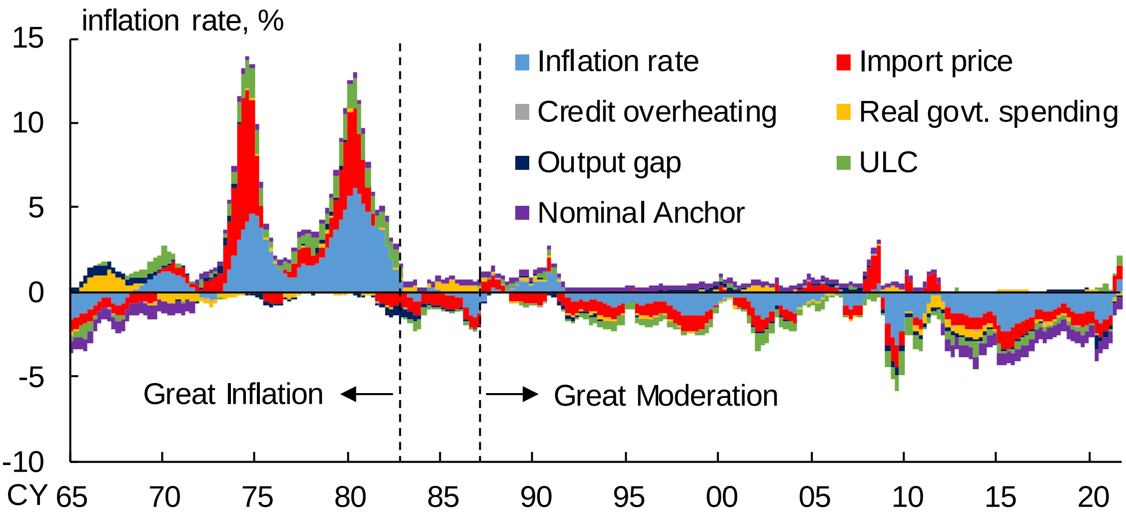


Note: Charts for Germany and the United Kingdom start from 1971Q1 and 1971Q4 respectively.

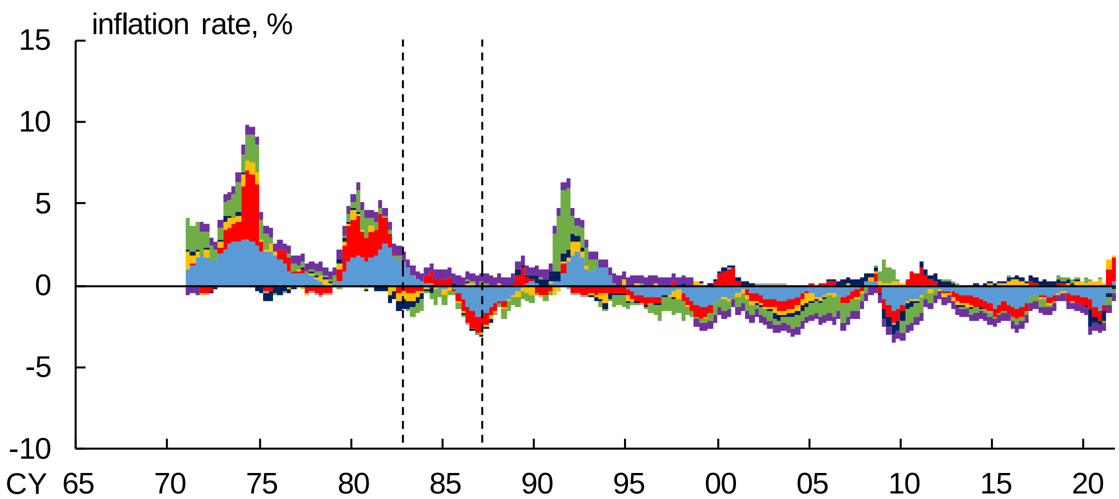
Source: Authors' calculation based on data from Haver.

Chart 7: Decomposition of One-year-ahead IaR_{90}

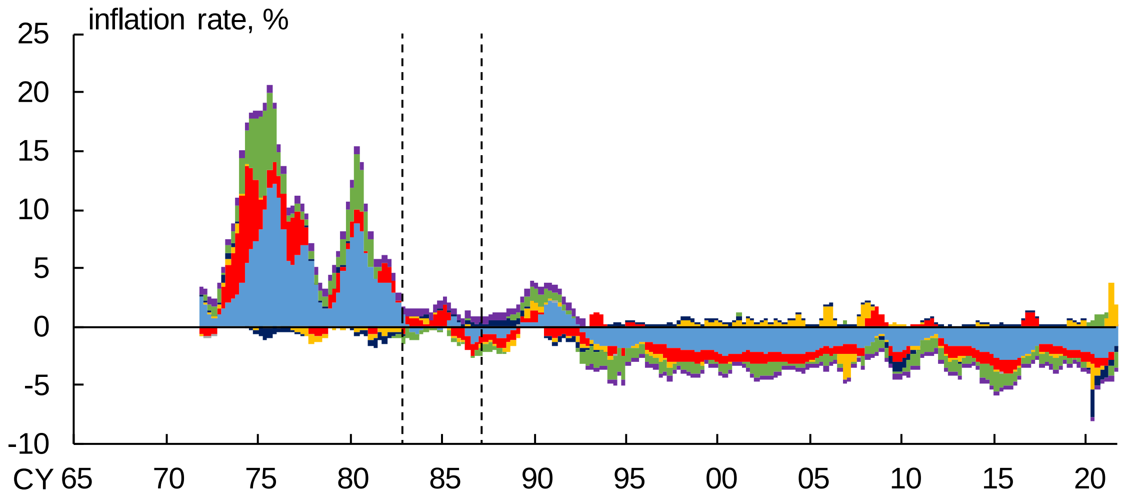
(a) the United States



(b) Germany



(c) the United Kingdom

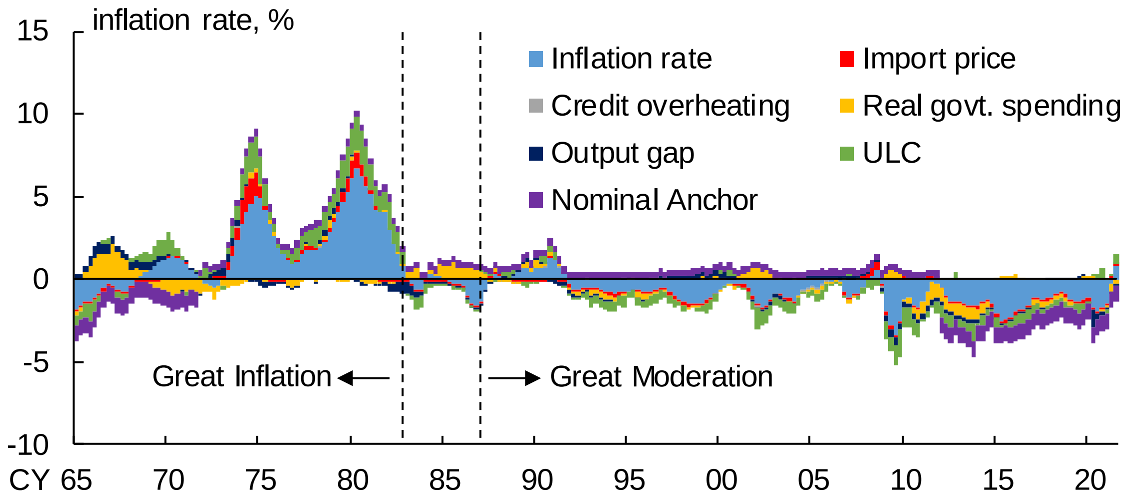


Note: Figures show the deviation from the historical average. Charts for Germany and the United Kingdom start from 1971Q1 and 1971Q4 respectively.

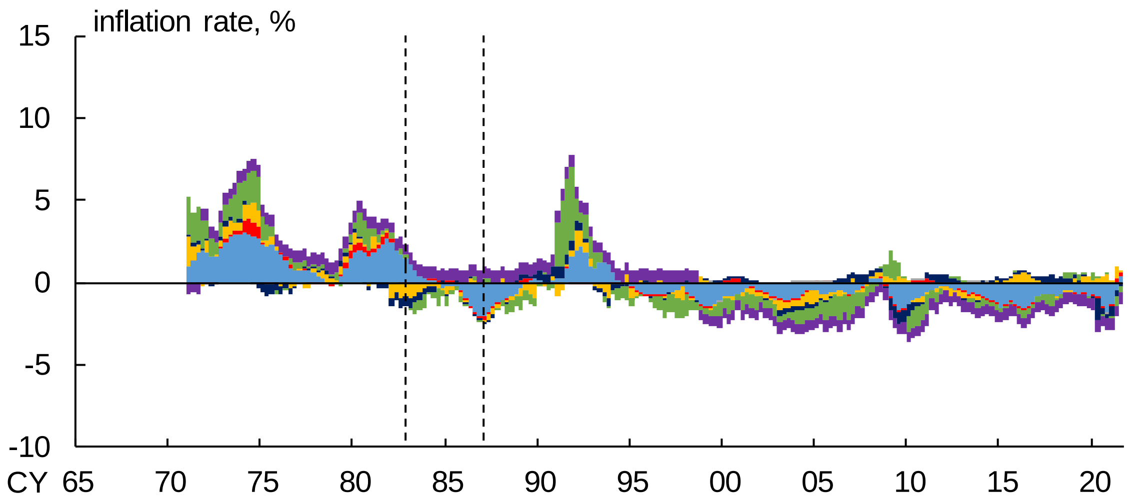
Source: Authors' calculation based on data from Haver.

Chart 8: Decomposition of Two-year-ahead IaR_{90}

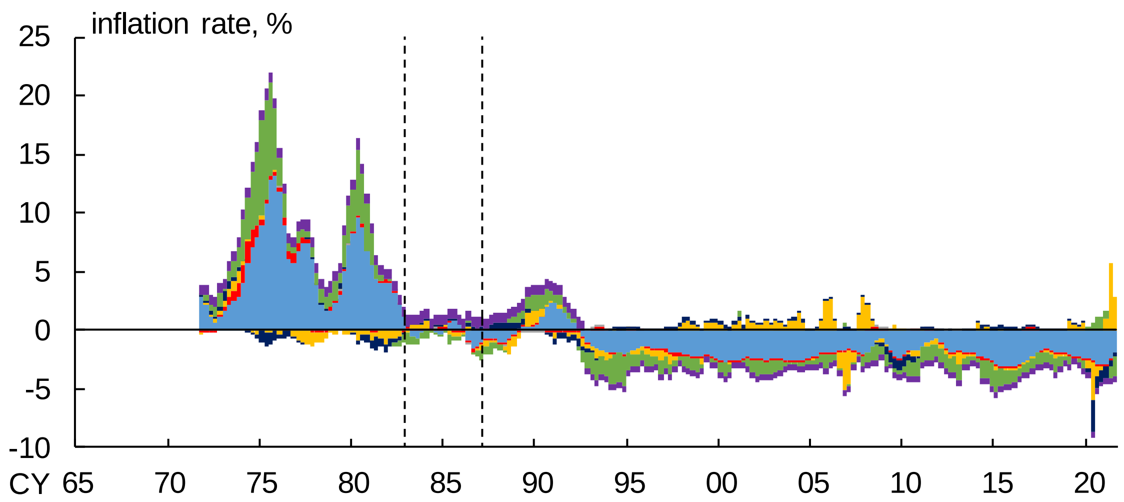
(a) the United States



(b) Germany



(c) the United Kingdom

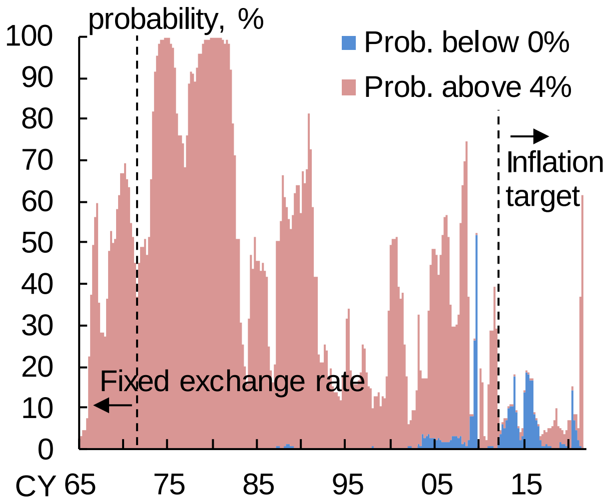


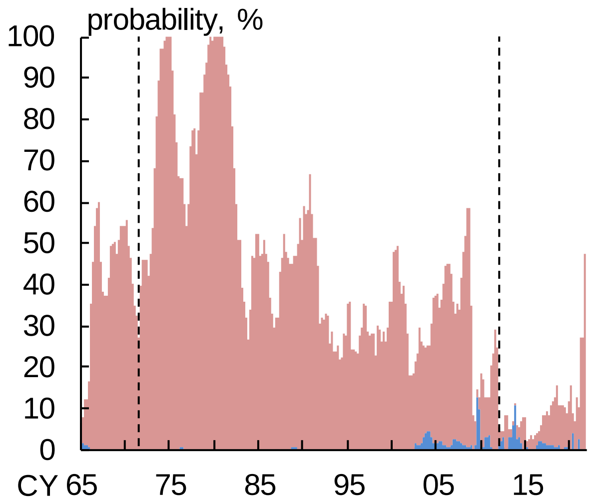
Note: Figures show the deviation from the historical average. Charts for Germany and the United Kingdom start from 1971Q1 and 1971Q4 respectively.

Source: Authors' calculation based on data from Haver.

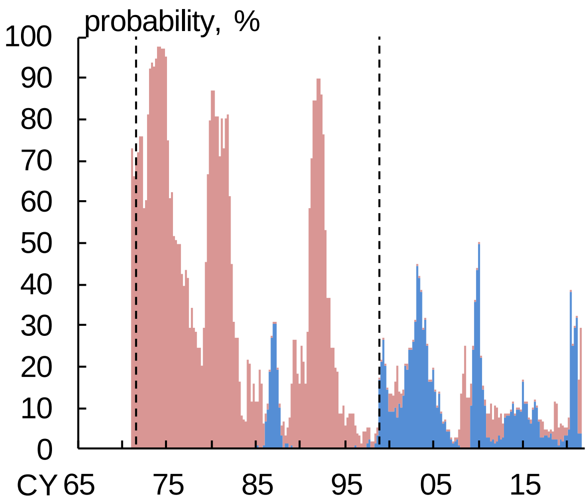
Chart 9: Probability of Rising and Falling Inflation

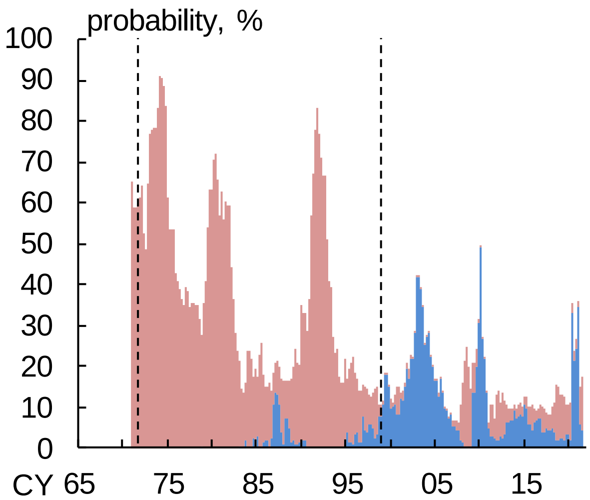
(a) the United States (LHS: 1-year ahead, RHS: 2-year ahead)



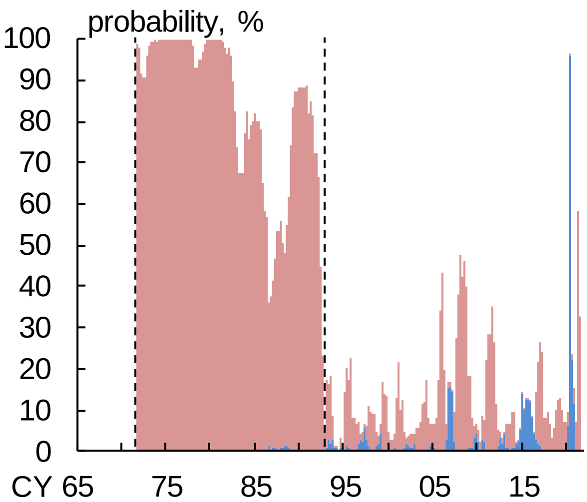


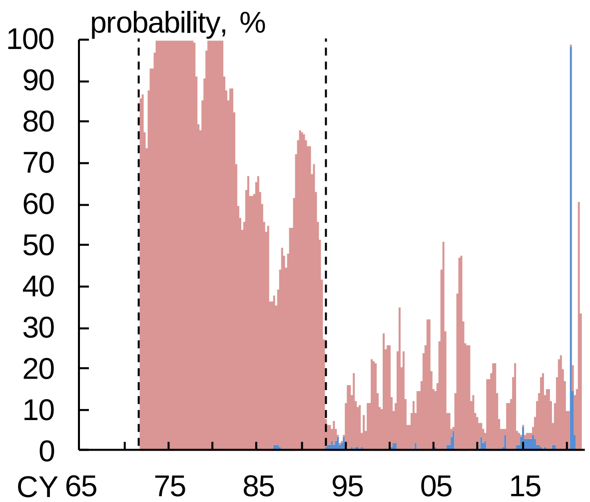
(b) Germany (LHS: 1-year ahead, RHS: 2-year ahead)





(c) the United Kingdom (LHS: 1-year ahead, RHS: 2-year ahead)





Note: Charts for Germany and the United Kingdom start from 1971Q1 and 1971Q4 respectively.
Source: Authors' calculation based on data from Haver.

Table 3: Estimation Results of Panel Quantile Regression – One-year-ahead Inflation –

Dependent Variable: One-year-ahead Inflation Rate

	Model 1 Baseline			Model 2 Extending for ULC			Model 3 Extending for Govt. Spending			Model 4 Extending for Govt. Spending		
Quantile	10%	50%	90%	10%	50%	90%	10%	50%	90%	10%	50%	90%
Unit Labor Cost (ULC)	0.06 **	0.12 ***	0.23 ***	—	—	—	0.06 **	0.10 ***	0.24 ***	0.06 **	0.11 ***	0.23 ***
ULC (High Import-to-GDP ratio)	—	—	—	-0.04	-0.02	0.00	—	—	—	—	—	—
ULC (Low Import-to-GDP ratio)	—	—	—	0.13 ***	0.19 ***	0.44 ***	—	—	—	—	—	—
Real Government Spending (RGS)	0.12 ***	0.11 ***	0.13 ***	0.11 ***	0.09 ***	0.12 ***	—	—	—	—	—	—
RGS (Govt. Debt above Average)	—	—	—	—	—	—	0.10 ***	0.10 ***	0.09 ***	—	—	—
RGS (Govt. Debt below Average)	—	—	—	—	—	—	0.12 **	0.11 **	0.13	—	—	—
RGS (Govt. Debt above +1σ)	—	—	—	—	—	—	—	—	—	0.05 ***	0.04 ***	0.20 ***
RGS (Govt. Debt below +1σ)	—	—	—	—	—	—	—	—	—	0.12	0.11	0.13
Import Price (above Average)	0.04	0.09 ***	0.19 ***	0.04	0.08 ***	0.14 ***	0.05	0.11 ***	0.20 ***	0.05	0.11 ***	0.20 ***
Import Price (below Average)	0.05 **	0.02 *	0.05 **	0.06 **	0.01	0.04 **	0.03 *	0.01 *	0.04 **	0.04 *	0.02 *	0.05 **
Persistence of Credit Overheating	-0.59	0.13	0.08	-0.55	0.23	0.45	-0.55	0.17	0.11	-0.57	0.21	0.03
Lag of Inflation	0.41 ***	0.52 ***	0.59 ***	0.34 ***	0.46 ***	0.45 ***	0.38 ***	0.51 ***	0.53 ***	0.38 ***	0.50 ***	0.54 ***
Output Gap	0.06 *	0.09 **	0.09 *	0.07 *	0.10 **	0.11 ***	0.06	0.08 *	0.08	0.06 *	0.08	0.09
Dummy for Nominal Anchor		Yes			Yes			Yes			Yes	
Country Fixed Effects		Yes			Yes			Yes			Yes	
Observations		1,967			1,967			1,861			1,861	

Note: ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively. The confidence intervals are obtained using the block bootstrap method.

Source: Authors' calculation based on data from Haver.

Table 4: Estimation Results of Panel Quantile Regression – Two-year-ahead Inflation –

Dependent Variable: Two-year-ahead Inflation Rate

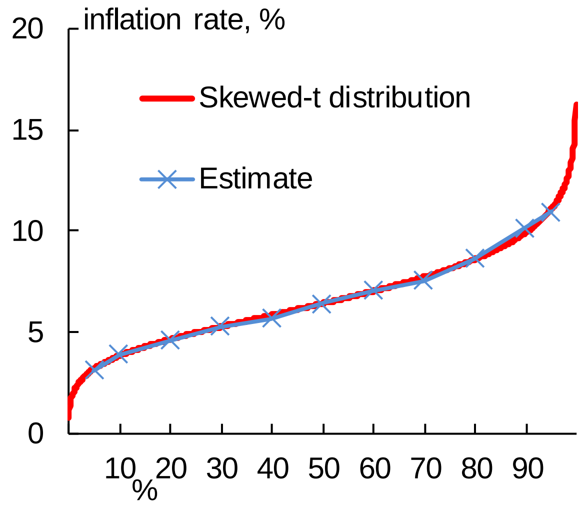
	Model 1 Baseline			Model 2 Extending for ULC			Model 3 Extending for Govt. Spending			Model 4 Extending for Govt. Spending		
Quantile	10%	50%	90%	10%	50%	90%	10%	50%	90%	10%	50%	90%
Unit Labor Cost (ULC)	0.09 **	0.13 ***	0.27 ***	—	—	—	0.08 *	0.13 ***	0.33 ***	0.09 *	0.13 ***	0.32 ***
ULC (High Import-to-GDP ratio)	—	—	—	-0.04	-0.02	0.02	—	—	—	—	—	—
ULC (Low Import-to-GDP ratio)	—	—	—	0.13 ***	0.26 ***	0.54 ***	—	—	—	—	—	—
Real Government Spending (RGS)	0.08 ***	0.13 ***	0.20 **	0.09 ***	0.14 ***	0.14 *	—	—	—	—	—	—
RGS (Govt. Debt above Average)	—	—	—	—	—	—	0.12 ***	0.16 ***	0.14 *	—	—	—
RGS (Govt. Debt below Average)	—	—	—	—	—	—	0.07 **	0.11 **	0.21	—	—	—
RGS (Govt. Debt above +1σ)	—	—	—	—	—	—	—	—	—	0.16 ***	0.14 ***	0.34 **
RGS (Govt. Debt below +1σ)	—	—	—	—	—	—	—	—	—	0.07	0.12	0.17
Import Price (above Average)	0.02	0.06 **	0.04	0.02	0.05 *	0.04	0.03 *	0.08 **	0.08	0.03 *	0.08 **	0.08
Import Price (below Average)	-0.01	0.01	0.00	-0.01	0.01	-0.01	-0.01	0.01	-0.01	-0.01	0.00	0.02
Persistence of Credit Overheating	-0.50 *	-0.34	-0.04	-0.45 *	-0.12	0.00	-0.52 *	-0.32	-0.11	-0.55 *	-0.29	-0.17
Lag of Inflation	0.30 ***	0.39 ***	0.64 **	0.26 ***	0.26 ***	0.45 ***	0.29 ***	0.35 ***	0.49 *	0.27 ***	0.36 ***	0.52 **
Output Gap	0.06 *	0.09 *	0.11	0.08 *	0.08 *	0.10 **	0.06	0.07	0.10	0.06	0.08	0.08
Dummy for Nominal Anchor		Yes			Yes			Yes			Yes	
Country Fixed Effects		Yes			Yes			Yes			Yes	
Observations		1,967			1,967			1,861			1,861	

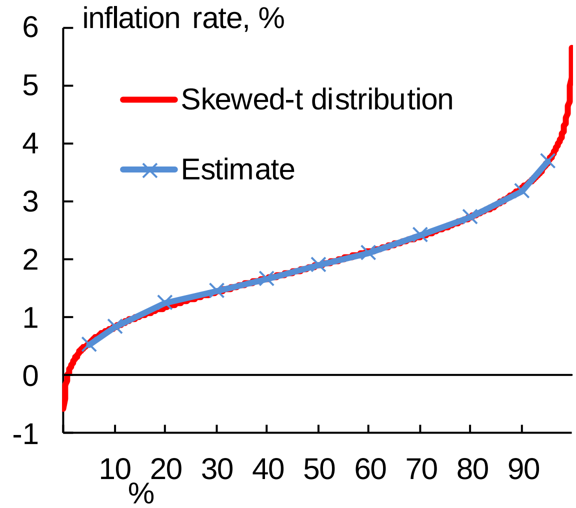
Note: ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively. The confidence intervals are obtained using the block bootstrap method.

Source: Authors' calculation based on data from Haver.

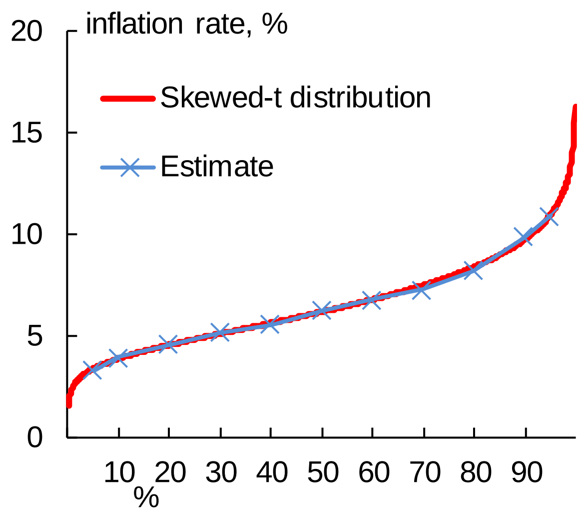
Appendix Chart A1.1: Estimated Quantiles and Fitted Skewed-*t* Quantiles
– One-year-ahead Inflation Distribution –

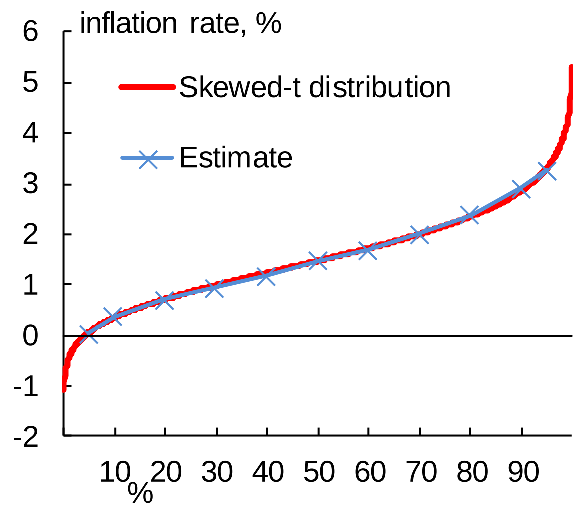
(a) the United States (LHS: 1970-1974, RHS: 2015-2019)



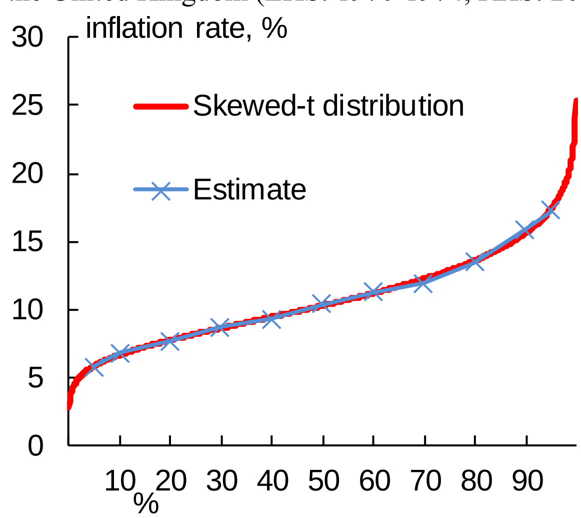


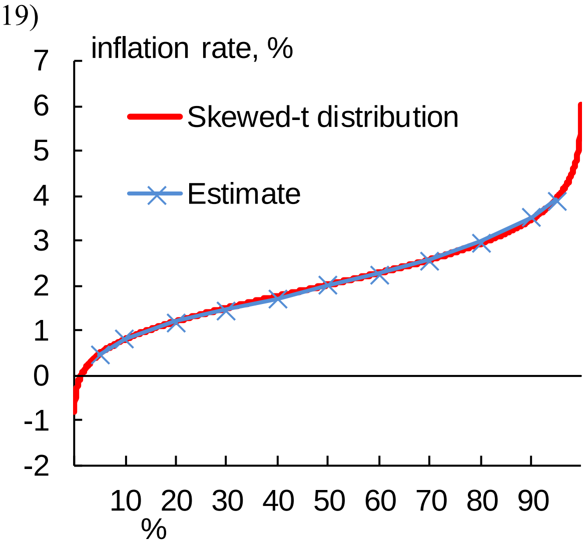
(b) Germany (LHS: 1970-1974, RHS: 2015-2019)





(c) the United Kingdom (LHS: 1970-1974, RHS: 2015-2019)

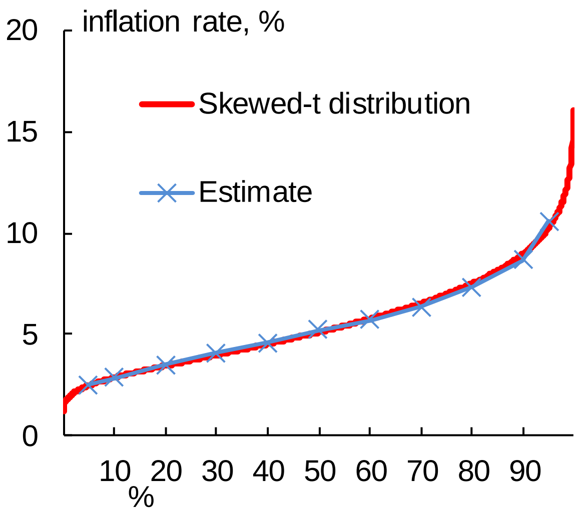


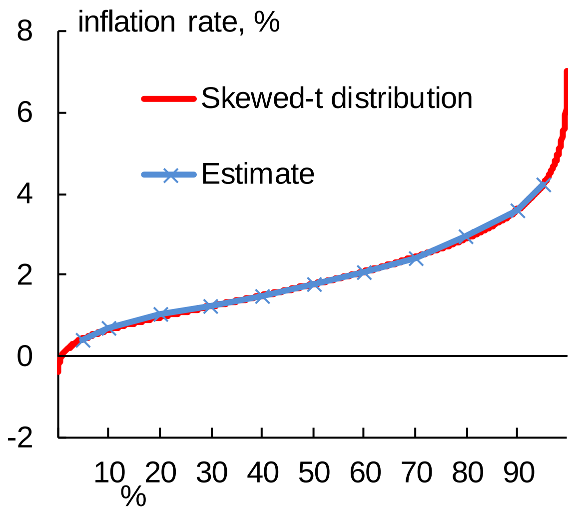


Source: Authors' calculation based on data from Haver.

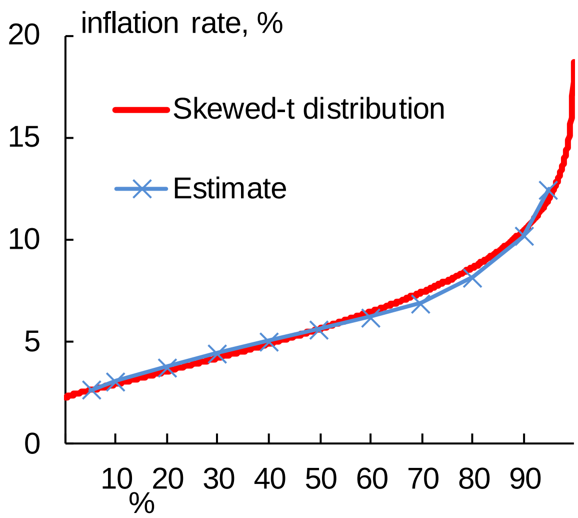
Appendix Chart A1.2: Estimated Quantiles and Fitted Skewed-*t* Quantiles
– Two-year-ahead Inflation Distribution –

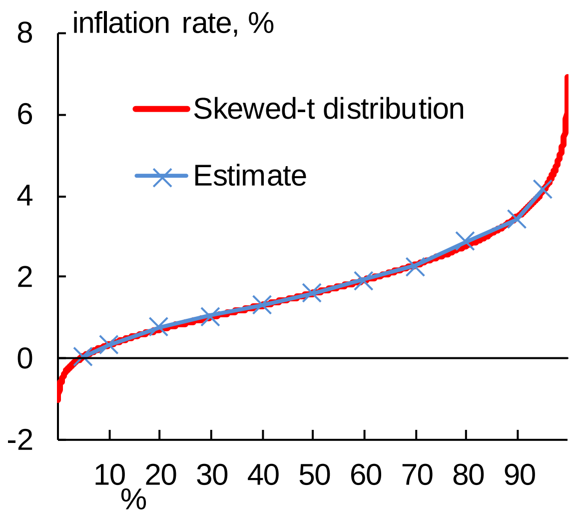
(a) the United States (LHS: 1970-1974, RHS: 2015-2019)



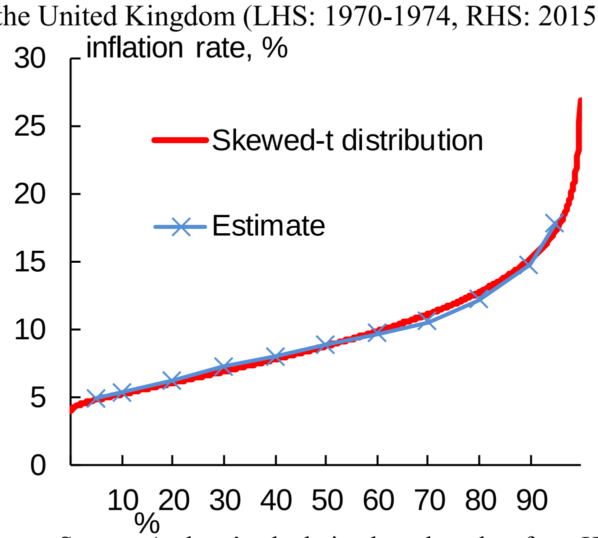


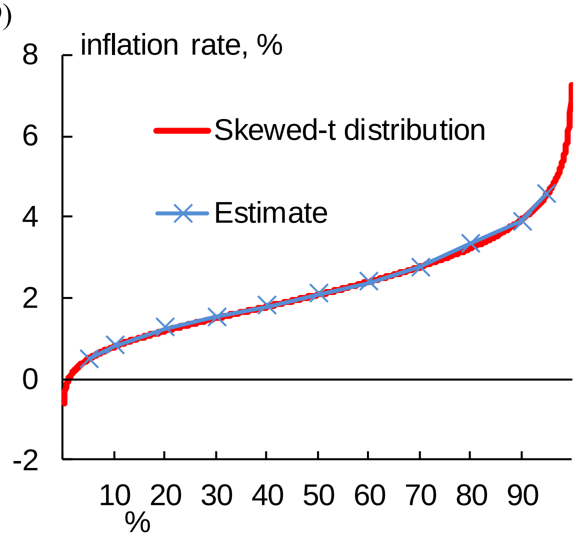
(b) Germany (LHS: 1970-1974, RHS: 2015-2019)





(c) the United Kingdom (LHS: 1970-1974, RHS: 2015-2019)





Source: Authors' calculation based on data from Haver.

Appendix Table A1.1: Estimation Results of Panel Quantile Regression – One-year-ahead Inflation –

Dependent Variable: One-year-ahead Inflation Rate

	5%	10%	20%	30%	40%	50%	60%	70%	80%	90%	95%
Unit Labor Cost	0.03 *	0.06 **	0.06 ***	0.08 ***	0.08 ***	0.12 ***	0.14 ***	0.14 ***	0.18 ***	0.23 ***	0.21 ***
	[0.01, 0.14]	[0.02, 0.13]	[0.02, 0.12]	[0.04, 0.12]	[0.05, 0.14]	[0.06, 0.16]	[0.07, 0.18]	[0.08, 0.22]	[0.1, 0.27]	[0.11, 0.3]	[0.11, 0.33]
Real Government Spending	0.13 ***	0.12 ***	0.11 ***	0.10 ***	0.10 ***	0.11 ***	0.09 ***	0.09 ***	0.10 ***	0.13 ***	0.18 ***
	[0.07, 0.16]	[0.09, 0.16]	[0.08, 0.14]	[0.07, 0.13]	[0.06, 0.13]	[0.06, 0.14]	[0.05, 0.14]	[0.05, 0.14]	[0.06, 0.16]	[0.07, 0.21]	[0.1, 0.28]
Import Price (above Average)	0.02	0.04	0.05 **	0.06 ***	0.06 ***	0.09 ***	0.11 ***	0.11 ***	0.15 ***	0.19 ***	0.17 ***
	[-0.05, 0.07]	[-0.01, 0.07]	[0.02, 0.09]	[0.02, 0.1]	[0.03, 0.11]	[0.04, 0.12]	[0.05, 0.14]	[0.07, 0.17]	[0.08, 0.2]	[0.08, 0.23]	[0.08, 0.24]
Import Price (below Average)	0.07 **	0.05 **	0.03 **	0.03 **	0.03 **	0.02 *	0.02 *	0.02 *	0.03 *	0.05 **	0.05 **
	[0.01, 0.09]	[0.02, 0.09]	[0.01, 0.07]	[0.01, 0.07]	[0.01, 0.06]	[0.0, 0.06]	[0.0, 0.05]	[0.0, 0.06]	[0.0, 0.06]	[0.01, 0.09]	[0.02, 0.1]
Persistence of	-1.31	-0.59	-0.26	-0.12	0.08	0.13	0.16	0.13	0.07	0.08	0.22
Credit Overheating	[-2.59, 0.04]	[-1.75, 0.13]	[-0.82, 0.4]	[-0.64, 0.55]	[-0.45, 0.59]	[-0.33, 0.57]	[-0.29, 0.54]	[-0.3, 0.52]	[-0.48, 0.55]	[-0.65, 0.78]	[-0.72, 1.06]
Lag of Inflation	0.42 ***	0.41 ***	0.48 ***	0.51 ***	0.54 ***	0.52 ***	0.53 ***	0.57 ***	0.55 ***	0.59 ***	0.74 ***
	[0.32, 0.49]	[0.34, 0.5]	[0.4, 0.55]	[0.43, 0.59]	[0.44, 0.6]	[0.45, 0.62]	[0.45, 0.64]	[0.45, 0.67]	[0.43, 0.72]	[0.42, 0.84]	[0.48, 0.95]
Output Gap	0.06 *	0.06 *	0.06 *	0.07 **	0.08 **	0.09 **	0.09 *	0.09 **	0.09 *	0.09 *	0.07 *
	[0.0, 0.16]	[0.0, 0.15]	[0.01, 0.13]	[0.02, 0.13]	[0.02, 0.14]	[0.02, 0.16]	[0.01, 0.17]	[0.01, 0.18]	[0.01, 0.2]	[0.0, 0.2]	[0.0, 0.18]
Dummy for Nominal Anchor						Yes					
Country Fixed Effects						Yes					
Observations						1,967					

Note: The values in the square bracket show the 5 to 95 percent confidence intervals obtained using the block bootstrap method. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.
Source: Authors' calculation based on data from Haver.

Appendix Table A1.2: Estimation Results of Panel Quantile Regression – Two-year-ahead Inflation –

Dependent Variable: Two-year-ahead Inflation Rate

	5%	10%	20%	30%	40%	50%	60%	70%	80%	90%	95%
Unit Labor Cost	0.08 *	0.09 **	0.08 ***	0.09 ***	0.11 ***	0.13 ***	0.15 ***	0.17 ***	0.21 ***	0.27 ***	0.38 ***
	[0.01, 0.14]	[0.02, 0.14]	[0.04, 0.15]	[0.05, 0.17]	[0.05, 0.18]	[0.06, 0.21]	[0.07, 0.24]	[0.08, 0.28]	[0.09, 0.33]	[0.12, 0.45]	[0.15, 0.53]
Real Government Spending	0.08 ***	0.08 ***	0.09 ***	0.10 ***	0.11 ***	0.13 ***	0.14 ***	0.14 **	0.15 **	0.20 **	0.23 ***
	[0.05, 0.12]	[0.05, 0.12]	[0.05, 0.13]	[0.05, 0.16]	[0.05, 0.18]	[0.05, 0.19]	[0.05, 0.2]	[0.04, 0.23]	[0.04, 0.27]	[0.06, 0.31]	[0.07, 0.4]
Import Price (above Average)	0.03	0.02	0.02	0.03	0.04 *	0.06 **	0.06 **	0.07 *	0.06	0.04	0.07
	[-0.0, 0.04]	[-0.0, 0.05]	[-0.01, 0.06]	[-0.0, 0.07]	[0.0, 0.09]	[0.01, 0.1]	[0.01, 0.11]	[0.01, 0.12]	[-0.01, 0.13]	[-0.04, 0.16]	[-0.06, 0.22]
Import Price (below Average)	-0.03	-0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.03
	[-0.05, 0.02]	[-0.03, 0.03]	[-0.02, 0.04]	[-0.01, 0.05]	[-0.02, 0.05]	[-0.02, 0.05]	[-0.02, 0.05]	[-0.04, 0.06]	[-0.06, 0.08]	[-0.06, 0.11]	[-0.07, 0.14]
Persistence of	-0.79 *	-0.50 *	-0.52	-0.48	-0.39	-0.34	0.04	0.10	-0.17	-0.04	-0.37
Credit Overheating	[-1.62, -0.13]	[-1.11, -0.06]	[-0.99, 0.06]	[-0.98, 0.19]	[-0.96, 0.45]	[-0.95, 0.63]	[-0.92, 0.68]	[-0.91, 0.67]	[-1.06, 0.65]	[-1.49, 0.77]	[-1.87, 0.77]
Lag of Inflation	0.31 ***	0.30 ***	0.34 ***	0.38 ***	0.40 ***	0.39 ***	0.40 ***	0.43 ***	0.49 ***	0.64 **	0.58 **
	[0.21, 0.41]	[0.23, 0.41]	[0.26, 0.46]	[0.28, 0.49]	[0.29, 0.52]	[0.28, 0.54]	[0.28, 0.6]	[0.28, 0.69]	[0.28, 0.8]	[0.23, 0.93]	[0.21, 1.05]
Output Gap	0.05	0.06 *	0.09 *	0.11 *	0.11 *	0.09 *	0.10 *	0.10	0.13	0.11	0.10
	[-0.01, 0.13]	[0.0, 0.15]	[0.01, 0.17]	[0.01, 0.18]	[0.01, 0.18]	[0.01, 0.19]	[0.0, 0.21]	[-0.0, 0.24]	[-0.01, 0.27]	[-0.02, 0.28]	[-0.06, 0.28]
Dummy for Nominal Anchor						Yes					
Country Fixed Effects						Yes					
Observations						1,967					

Note: The values in the square bracket show the 5 to 95 percent confidence intervals obtained using the block bootstrap method. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.
Source: Authors' calculation based on data from Haver.