THE RISK OF INFLATION DISPERSION IN THE EURO AREA

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Abstract. We introduce a novel approach to measuring the risk of inflation dispersion across euro area countries. Our measure captures the dissimilarity between the full predictive inflation distributions of member states and thus reflects how 'far apart' inflation levels are expected to be. We show that the risk of inflation dispersion exhibits countercyclical behavior, rising during economic downturns. The main driver of this risk is the deterioration of financial conditions, whereas a robust anchoring of inflation expectations in each country serves to dampen it. Furthermore, we demonstrate that monetary policy loses effectiveness when dispersion risk is high: a contractionary monetary policy shock has only half the impact on output and prices compared to periods of low risk.

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I. Introduction

The resurgence of inflation in the euro area, spurred by the post-COVID crisis recovery and tensions in oil and natural gas markets following the war in Ukraine, has coincided with a significant increase in inflation differentials between member countries. These differentials, measured by the cross-country standard deviation in annual inflation rates across euro area members, have reached either unprecedented levels (HICP) or near all-time highs (HICP excluding food and energy), as depicted in Figure 1.

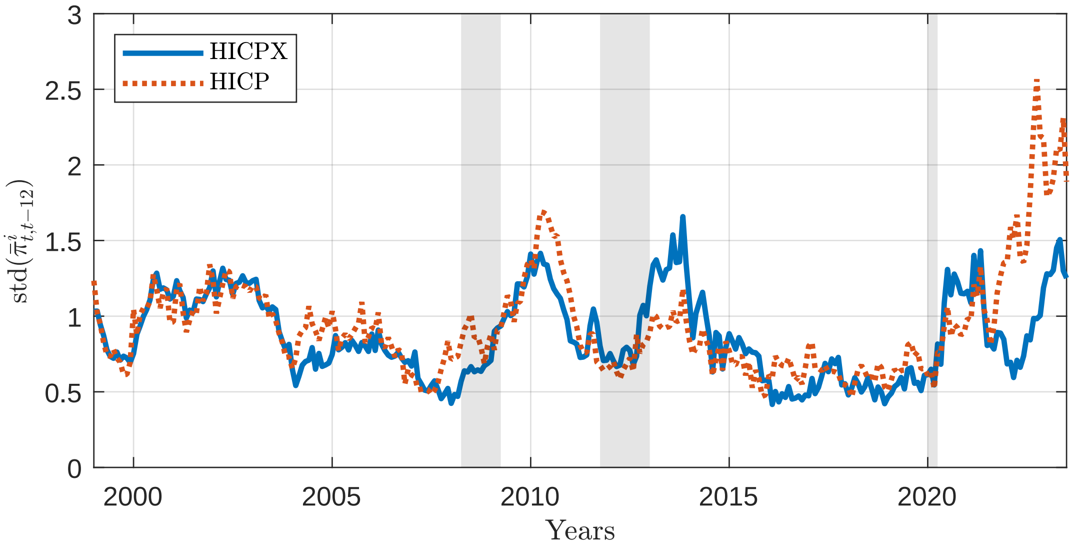
Accurately assessing the risk of inflation dispersion, as well as its determinants, is of deep relevance for policymakers because such a risk can challenge the effectiveness of monetary policy.[1] Adjusting nominal interest rates based on a single inflation target might result in an excessively accommodative monetary policy for nations experiencing notably higher inflation than the euro area average. Conversely, countries with inflation considerably below the average may encounter unwarranted tightening policy pressures. Furthermore, in the context of a monetary union, where countries share the same nominal interest rate, a high dispersion of inflation expectations translates into a high dispersion of real interest rates between member countries. Therefore, the risk of inflation dispersion reflects undoubtedly a risk of financial fragmentation in the euro area, which can impair the transmission of monetary policy (e.g., Cœuré, 2019).

In order to properly build a measure of expected inflation dispersion among euro area countries, one needs to take a probabilistic forecasting approach by considering not only cross-country differences in point forecasts of inflation, but also cross-country differences in density forecasts since they bring additional information, namely differentials in uncertainty and tail risks. This is what we intend to do in this paper.[2] More specifically, our dispersion measure reflects the dissimilarity, i.e., the distance, between the full predictive inflation

[1]For example, in the monetary policy statement of July, 27$^{\text{th}}$ 2023, Christine Lagarde expressed her concern about the heterogeneity in inflation between euro are members: "*The numbers that we see now for Spain, with inflation trending towards 2% and hopefully sustainably so, plus unemployment numbers that are as low as they have ever been, is a good set of numbers for the country and for the economy at large. It is not the same for all Member States and there are Member States where inflation is still very high and has been high and is expected to remain high for longer. So we have to be very attentive to the aggregate numbers. Those are the ones that are driving our inflation outlook, helping us determine our policy. But we also have to look at each Member State and the characteristics of each Member State. We shall see.*"

[2]This supplements current available measures of inflation dispersion typically rely on realized inflation, and thus, by construction, do not contain any forward-looking information about expected inflation dispersion at medium and long-term horizons. The ECB regularly publishes measures of inflation dispersion for the euro area using realized inflation. See, for example, Issing et al. (2003) and Consolo et al. (2021).

FIGURE 1. Cross-sectional Standard Deviation of Inflation in the Euro Area



Note: The figure shows the cross-country unweighted standard deviation of annual inflation rates in the euro area. $\bar{\pi}^i_{t,t-12}$ denotes the average over the last twelve months of the monthly inflation rate (core and headline inflation rates, annualized) for the country i of the euro area (Twelve countries, fixed composition, Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain). HICP stands for Harmonised Index of Consumer Prices, and HICPX stands for HICP inflation excluding energy and food. The sample is January 1999 to July 2023. Grey shaded areas indicate CEPR-dated recessions.

distributions of euro area member countries. Therefore, it captures how "far" apart inflation levels are expected to be between euro area members for a given horizon. Our primary focus is on assessing expected inflation dispersion over a twelve-month horizon.

We employ a two-step method to estimate flexible parametric predictive distributions that account for skewness and heavy tails in inflation series. The first step estimates the distributions semi-parametrically using quantile Phillips curve regressions for the first twelve euro area members, and in which inflation drivers are unemployment gap, oil price, financial stress, past and expected inflation rates.[3] In the second step, each estimated quantile distribution is smoothed, each month, by interpolating between the estimated quantiles using the flexible skewed t-distribution along the lines of the work of Adrian, Boyarchenko, and Giannone (2019) on GDP growth, and more recently Lopez-Salido and Loria (2024) on inflation. This enables us to convert each empirical quantile distribution into an estimated conditional distribution of inflation. Then, we apply a generalization of the Kullback and Leibler (1951)

[3]Euro area countries used are: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain.

divergence (denoted KL divergence, hereafter) for calculating the average divergence between all predictive distributions. The resulting series captures the expected inflation divergence between euro area members, and thus reflects the risk of inflation dispersion among euro area countries.

Based on our measure of expected divergence at the twelve-month horizon, we provide evidence that the risk of inflation differentials shows a strong countercyclical pattern, which tends to rapidly increase during economic downturns. An examination of the sources contributing to this risk along three dimensions (quantile, macroeconomic driver, and country) reveals the following results. First, the risk of inflation dispersion arises more, on average, from variations in differences in the left tails of predictive inflation distributions than in the right tails. There are however specific periods like the Great Recession, where differences are due to the right tail of the distributions. Second, the rising risk of dispersion appears to be mainly associated with a deterioration in financial conditions. By contrast, a robust anchoring of inflation expectations tends to mitigate this risk. Third, we show that no single country is the only source of dispersion risks on average over time, but some countries as Greece and Ireland play a significant role in very specific episodes, like during the Great Recession and the sovereign debt crisis.

We then investigate whether the risk of inflation dispersion matters for the transmission of monetary policy. By estimating simple local projections as proposed by Jordà (2005), we document that monetary policy is less powerful when the risk of inflation dispersion is high. In particular, a one-standard deviation increase in the Jarociński and Karadi (2020)'s monetary policy surprises leads to a peak drop on industrial production of around 0.5 percent when the risk is high. In contrast, the effect of monetary policy is twice larger when the risk is low. Similarly, the response of prices appears to be much larger when the risk of dispersion is low.

Interestingly, this result aligns with recent research on the monetary policy implications of inflation disagreement at the household level. In particular, Dong et al. (2024) show that household inflation disagreement weakens the effects of monetary policy on consumption and inflation. Households with higher inflation expectations perceive lower real interest rates and thus borrow more aggressively, eventually hitting borrowing limits. Once constrained, they cannot adjust consumption as much in response to monetary policy changes. Higher inflation disagreement would lead to a larger share of borrowing-constrained agents, resulting in less policy effectiveness. A similar mechanism may operate at the cross-country level: if inflation expectation differentials are high, some countries' consumers and firms may hit borrowing constraints earlier, resulting in more sluggish responses of aggregate activity to changes in interest rates.

Relation to other studies. Our paper is related to the literature on inflation differentials, which has been a long-standing issue in the European Monetary Union. Inflation dispersion was an important issue in defining the ECB's strategy at its inception (e.g., Issing et al., 2003), as well as in the recent ECB's strategy review in 2021 as discussed in depth by Consolo et al. (2021) and Reichlin et al. (2021).[4] From a theoretical perspective, Benigno (2004), Benigno and López-Salido (2006) and Kekre (2022) characterize the optimal monetary policy in a currency union with heterogeneity between countries. Galí and Monacelli (2008), Duarte and Wolman (2008), and Ferrero (2009) consider the role of optimal fiscal policy in the analysis. From an empirical perspective, the literature has been mainly focused on the underlying causes of realized inflation differentials in the euro area. Notable examples include Angeloni and Ehrmann (2007), Beck, Hubrich, and Marcellino (2009), and Estrada, Galí, and López-Salido (2013). More recently, Checherita-Westphal, Leiner-Killinger, and Schildmann (2024) empirically study the role of fiscal policy on inflation differentials in the EMU. We revisit this literature using our forward-looking measure of expected inflation divergence between euro area countries, which contain information not covered by divergence measures using realized inflation.

We also contribute to the literature on the estimation of the Phillips curve in the euro area. Galí, Gertler, and López-Salido (2001) show that standard Phillips curve fits euro area data very well. Ball and Mazumder (2021) reveal that a non-negligible role of inflation expectations and output gap in driving core inflation fluctuations in the euro area. Eser et al. (2020) give a broad picture of the implication of the Phillips curve analysis in the euro area for the conduct of ECB's monetary policy. In line with our paper, Baba et al. (2023) study the key drivers of the 2020-22 inflation surge across Europe and its dispersion across countries. All of these study examine the response of the conditional mean of euro area

[4]As often reminded by the ECB, inflation differentials per see may not be detrimental to the monetary union if they reflect the process of nominal convergence and economic development catch up.

inflation to economic conditions. Our paper offers evidence that economic factors are still at work in the tails, but in a heterogeneous way between euro area countries.

Our paper falls also within the growing body of literature studying macroeconomic risks initiated by Adrian, Boyarchenko, and Giannone (2019); see also among others Plagborg-Møller et al. (2020), Figueres and Jarociński (2020), Adrian et al. (2022), Hilscher, Raviv, and Reis (2022), and Lopez-Salido and Loria (2024). Adrian, Boyarchenko, and Giannone (2019) estimate the conditional distribution of U.S. GDP growth as a function of economic and financial conditions using quantile regressions.[5] While this literature has focused on the predictive distributions of one single economic variable (such as GDP growth or inflation) with a particular emphasis on tail risks, we extend it in some way to the question of the heterogeneity of these distributions between countries by building our measure of KL divergence. Interestingly, Korobilis and Schröder (2024) develop a multicountry quantile factor augmented vector autoregression (QFAVAR) to capture heterogeneities both across euro area countries and across characteristics of the predictive distributions. However, the question of the degree of divergence is not addressed.

The rest of the paper is organized as follows. Section II presents quantile Phillips curve for each euro area countries, and discuss cross-country dispersion of parameters. Section III present and apply our approach to measure the risk of inflation dispersion. Section IV discusses the sources of inflation disperion risk by quantile, by inflation driver, and by country. Section V presents the policy implications. Section VI concludes.

II. Quantile National Phillips Curve

II.1. **Phillips Curve Quantile Regressions.** We rely on quantile regression models for studying the determinants of cross-country dispersion of the entire distribution of inflation. We follow the empirical strategy developed by Lopez-Salido and Loria (2024).[6] The key difference is that we apply this strategy to the first twelve countries of the euro area, instead of the euro area as a whole.

[5]Macroeconomic tail risks can also be studied through the lens of Markov-switching models, as in Caldara et al. (2021) in the U.S. and Lhuissier (2022) in the euro area.

[6]The paper considers U.S economy, euro area but also a panel of OECD countries. See also Busetti, Caivano, and Rodano (2015) and Chortareas, Magonis, and Panagiotidis (2012) for the estimation of quantile Phillips curve for the euro area as a whole.

Let us denote by $\pi^i_{t+1,t+1+h}$ the year-on-year growth rate of monthly Harmonized Index of Consumer Prices excluding food and energy (HICPX) between $t+1$ and $t+1+h$ for country i, and by x^i_t a $1 \times k$-dimensional vector containing the conditioning variables for country i, including a constant. Our benchmark horizon is $h = 12$, that is the average inflation over the next year, starting in month $t+1$ at time t. We consider a linear model for the conditional inflation quantiles whose predicted value:

$$\hat{Q}_\tau(\pi^i_{t+1,t+1+h}|x^i_t) = x^i_t\hat{\beta}^i_\tau, \tag{1}$$

is a consistent linear estimator of the quantile function of $\pi^i_{t+1,t+1+h}$ conditional on x^i_t, where $\tau \in (0, 100)$ is the quantile expressed in percentage, $\hat{\beta}^i_\tau$ is a $k \times 1$-dimensional vector of estimated quantile-specific parameters. More specifically, our quantile regression model for inflation is as follows:

$$\begin{aligned}\hat{Q}_\tau(\pi^i_{t+1,t+1+h}|x^i_t) = \hat{\mu}^i_\tau + \left(1 - \hat{\lambda}^i_\tau\right)\pi^i_{t-12,t} + \hat{\lambda}^i_\tau\pi^{LTE,i}_t \\ + \hat{\theta}^i_\tau\left(u^i_t - u^{*,i}_t\right) + \hat{\gamma}^i_\tau\left(\pi^o_{t-12,t} - \pi^i_{t-12,t}\right) + \hat{\delta}^i_\tau s^i_t,\end{aligned} \tag{2}$$

where all variables are monthly time series covering January 1999 through July 2023.[7] Data sources are presented in the Appendix. We impose some constraints, based on the literature, and use the inequality constrained quantile regression method developed by Koenker and Ng (2005) for the estimation.

The variables $\pi^i_{t-12,t}$ and $\pi^{LTE,i}_t$ represent average inflation over the previous twelve months and a measure of long-term inflation expectations, respectively. The relative importance of both variables is determined by the parameter λ^i_τ, with $0 \leq \lambda^i_\tau \leq 1$, as in Galí and Gertler (1999), Blanchard, Cerutti, and Summers (2015) and Lopez-Salido and Loria (2024) among others. We use six- to ten-years-ahead inflation expectations from Consensus Economics as long-term inflation expectation series.[8]

Our second factor is the unemployment gap measured as the difference between the unemployment rate u^i_t and the non-accelerating wage rate of unemployment $u^{*,i}_t$ provided by the

[7]Our sample size aligns closely with other empirical studies examining the relationships between macroeconomic tail risks and financial conditions in the euro area. Notable examples include Figueres and Jarociński (2020) and Lopez-Salido and Loria (2024).

[8]As an alternative, inflation-linked swap (ILS) rates could be useful for deriving market-based measures of long-term inflation expectations. However, they are only available since 2004.

European Commission. The parameter θ^i_τ captures the slope of the Phillips curve at various inflation quantiles.

The third factor $\pi^o_{t-12,t} - \pi^i_{t-12,t}$ represents variations in relative oil price, where $\pi^o_{t-12,t}$ is the average inflation over the previous twelve months of crude oil price. This allows to capture the pass-through of oil prices into core inflation measures.[9] Our approach captures the effects of oil prices not only on the conditional mean of inflation, but on the entire inflation distribution. Cross-quantile and cross-country variations in the parameters γ^i_τ in equation (2) capture its effects.

The fourth factor s^i_t represents financial conditions. The literature has documented firms financing conditions also helps to explain inflation dynamics. Notable examples include Del Negro, Giannoni, and Schorfheide (2015), Christiano, Eichenbaum, and Trabandt (2015) and Gilchrist et al. (2017). More importantly, Lopez-Salido and Loria (2024) extend the analysis to consider the effect of financial conditions on the conditional distribution of inflation. Following these authors, we approximate s^i_t by the Composite Indicator of Systemic Stress (CISS), except for Luxembourg for which we use the Country-Level Index of Financial Stress (CLIFS).[10] The parameter associated with financial conditions in our empirical specification of the Phillips curve is δ^i_τ.

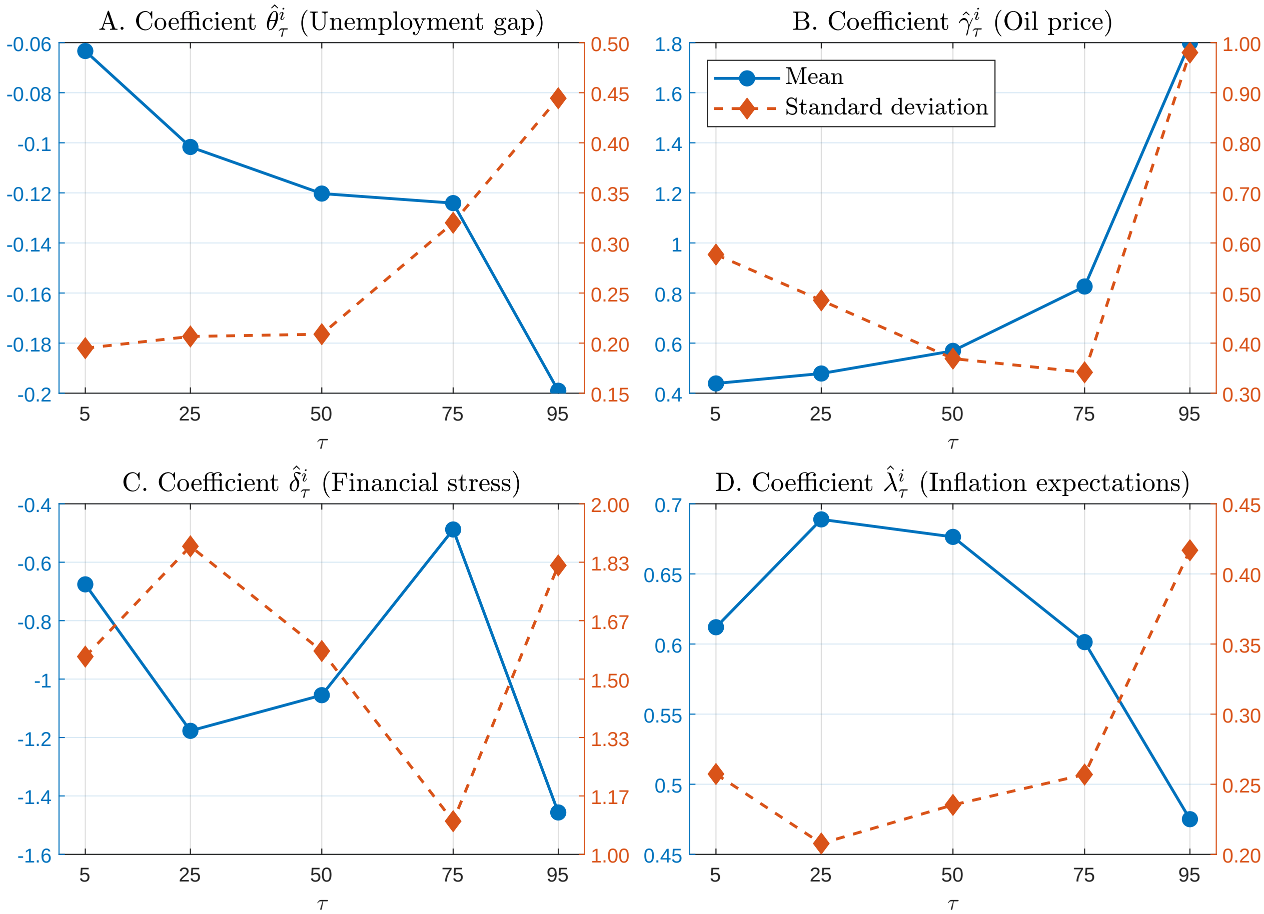
II.2. **Cross-country Heterogeneity of Phillips Curve parameters.** Figure 2 synthesizes the estimated coefficients across quantiles and countries. For each variable, it shows two different kinds of information on estimated coefficients. The first one is about the magnitude of the coefficient and the second one is about its cross-country dispersion. We provide a full description of results country-by-country in the Appendix B.

For the magnitude, we report the mean of the estimated coefficients for each quantile to determine to what extent the variable has a greater or lesser impact on inflation (in average for all countries) depending on the quantile considered. For the cross-country dispersion, we

[9] Blanchard, Cerutti, and Summers (2015) consider import-price inflation in their estimated Phillips curve, that is proxied by oil price inflation at a monthly frequency in Lopez-Salido and Loria (2024). We also consider commodity and energy prices instead of oil price using the above-described specification of the augmented quantile Phillips curve. The results are robust to the choice of the series and are not reported here.

[10] The CISS, developed by Kremer, Lo Duca, and Holló (2012), is a weekly index maintained by the ECB. It includes 15 raw series, mainly market-based financial stress measures that are split equally into five categories: financial intermediaries, money markets, equity markets, bond markets and foreign exchange markets. The CLIFS, proposed by Peltonen, Klaus, and Duprey (2015), follows the approach of the CISS, but with slightly different market segments.

Figure 2. Estimated Coefficients by Quantile: Magnitude and Dispersion

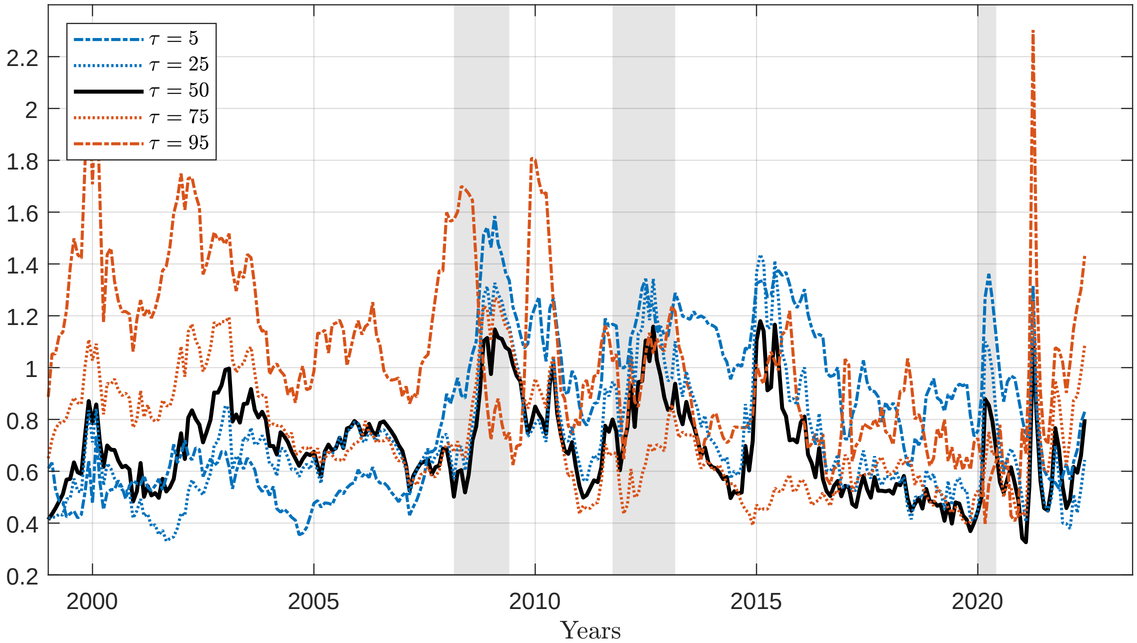


Note: For each estimated coefficient of the quantile regression defined by equation (2), the figure reports the unweighted mean of the estimated coefficients (blue solid line with circles) and the standard deviation (red dashed line with diamonds). For each panel, the title panel gives the symbol of the coefficient and the associated variable in parenthesis.

report the standard deviation of the estimated coefficients for each quantile to determine to what extent the impact of this variable on inflation is more or less dispersed across countries, depending on the quantile under consideration. Ultimately, we can identify the quantiles for which certain variables play an important role in inflation dynamics and are a source of structural heterogeneity between countries.

For unemployment gap, the figure suggests a steeper Phillips curve for higher quantiles: the average value of coefficients reaches its maximum for $\tau = 5$, with a value of -0.06, and its minimum at the quantile $\tau = 95$, with a value of -0.20. The cross-country dispersion of the estimated coefficients is the highest for the top quantile ($\tau = 95$). Unemployment gap can therefore be considered as a potential source of inflation dispersion risk at the upper tail

FIGURE 3. Dispersion of Conditional Quantiles



Note: Standard deviation of conditional inflation quantiles $\hat{Q}_\tau(\pi^i_{t+1,t+h}|x^i_t)$ across country i, for quantiles $\tau = \{5; 25; 50; 75; 95\}$ and forecast horizon $h = 12$. Grey shaded areas indicate CEPR-dated recessions.

of the distribution. For energy prices, the magnitude of estimated coefficients increases with the quantile considered, with a sharp increase between $\tau = 50$ and $\tau = 95$ (from 0.57 to 1.80). Estimated coefficients are less dispersed in the middle of the distribution than in the tails. This suggests that energy prices can therefore be considered as a source of inflation dispersion for both downward and upward inflation risks. Regarding financial stress, the average values of estimated coefficients are negative whatever the quantile considered. It suggests that financial stress is associated with downward inflation risks. We do not observe a clear pattern of the magnitude and cross-country dispersion of estimated coefficients according to the quantile. This suggests that financial stress may be responsible for inflation dispersion for all the predictive distributions. Finally, for inflation expectations, the magnitude of estimated coefficients exhibits an inverted U-shaped and decreases with the quantile while its cross-section dispersion increases. This result suggests that past inflation, weighted by $(1 - \lambda^i_\tau)$ in equation (2), can be interpreted as a potential source of dispersion for upward risks associated to the quantile $\tau = 95$.

II.3. **Cross-country Heterogeneity of Quantile Regressions.** Figure 3 depicts the evolution of the dispersion of conditional quantiles across countries for the one-year forecast horizon. Two stylized facts emerge. First, there is strong evidence of time variation in the cross-country dispersion of conditional quantiles. For any quantile, the dispersion tends to increase during economic downturns like the Great Recession, the sovereign debt crisis, and the Covid-19 crisis. Clearly, the dispersion is countercyclical. Second, there are significant differences in magnitude of variations across quantiles over time. The cross-country standard deviation of the 50$^{\text{th}}$ quantile appears to be always smaller than either the lower or the upper quantiles throughout the sample. This means that particular attention must be paid on tail risks when investigating cross-country divergence. In particular, inflation dispersion is clearly higher for the upper quantiles (75$^{\text{th}}$ and 95$^{\text{th}}$) than for other quantiles during the first decade of the euro area. This can be explained by the ongoing convergence process on the eve of the creation of the euro area with some countries that were still experiencing high levels of inflation. By contrast, from the Great Recession of 2008-09 to the COVID crisis, the situation is reversed. The highest inflation dispersions are associated with downside risk of inflation (5$^{\text{th}}$ and 25$^{\text{th}}$ quantiles).

To sum up, the evolution of the cross-country dispersion varies differently depending on the quantile. So focusing exclusively only on one particular quantile is not sufficiently informative about the degree of expected inflation dispersion among euro area countries. In the next section, we propose a unified measure that consider all quantiles of the distribution.

III. Measuring Divergence

This section relies on the quantile regression Phillips curve estimates to construct our measure of the risk of inflation dispersion. Section III.1 shows how we map the quantile regression estimates into a flexible distribution to recover a probability density function for each country. Section III.2 shows how our measure of divergence is computed using those distributions.

III.1. **The Conditional Inflation Distribution.**

The quantile regression (2) furnishes us with rough estimates of the quantile function, which represents an inverse cumulative distribution function. Following Adrian, Boyarchenko, and Giannone (2019), we map the quantile regression estimates into a skewed t-distribution to recover and show a probability density function. The skewed t-distribution was developed by Azzalini and Capitanio (2003) and has the following form:

$$f(\pi^i_{t+1,t+1+h}|x^i_t,\mu^i_t,\sigma^i_t,\eta^i_t,\kappa^i_t) = \frac{2}{\sigma^i_t} t(z^i_{t,t+h};\kappa^i_t) T\left(\eta^i_t z^i_{t,t+h}\sqrt{\frac{\kappa^i_t+1}{\kappa^i_t+(z^i_{t,t+h})^2}};\kappa^i_t+1\right),$$

where $z^i_{t,t+h} = \frac{\pi^i_{t+1,t+1+h}(x_t)-\mu^i_t}{\sigma^i_t}$, and $t(.)$ and $T(.)$ represent the density and cumulative distribution function of the student t-distribution, respectively. The four time-varying parameters of the distribution pin down the location μ^i_t, scale σ^i_t, shape η^i_t, and fatness κ^i_t for each country i, where η^i_t and κ^i_t parameters control the skewness and the kurtosis of the distribution, respectively. To simplify notations, we denote $f^{i,h}_t(\pi^i_{t+1,t+1+h}) \equiv f(\pi^i_{t+1,t+1+h}|x^i_t,\mu^i_t,\sigma^i_t,\eta^i_t,\kappa^i_t)$, the skewed t-distribution of predicted inflation over the next year in country i at time t.

For each month and each country, we choose the four parameters (μ^i_t, σ^i_t, η^i_t, κ^i_t) of the skewed t-distribution to minimize the squared distance between our estimated quantile function $\hat{Q}_\tau(\pi^i_{t+1,t+1+h}|x^i_t)$ obtained from the quantile Phillips curve model in equation (2) and the quantile function of the skew t-distribution to match the 5$^{\text{th}}$, 25$^{\text{th}}$, 75$^{\text{th}}$ and 95$^{\text{th}}$ quantiles.

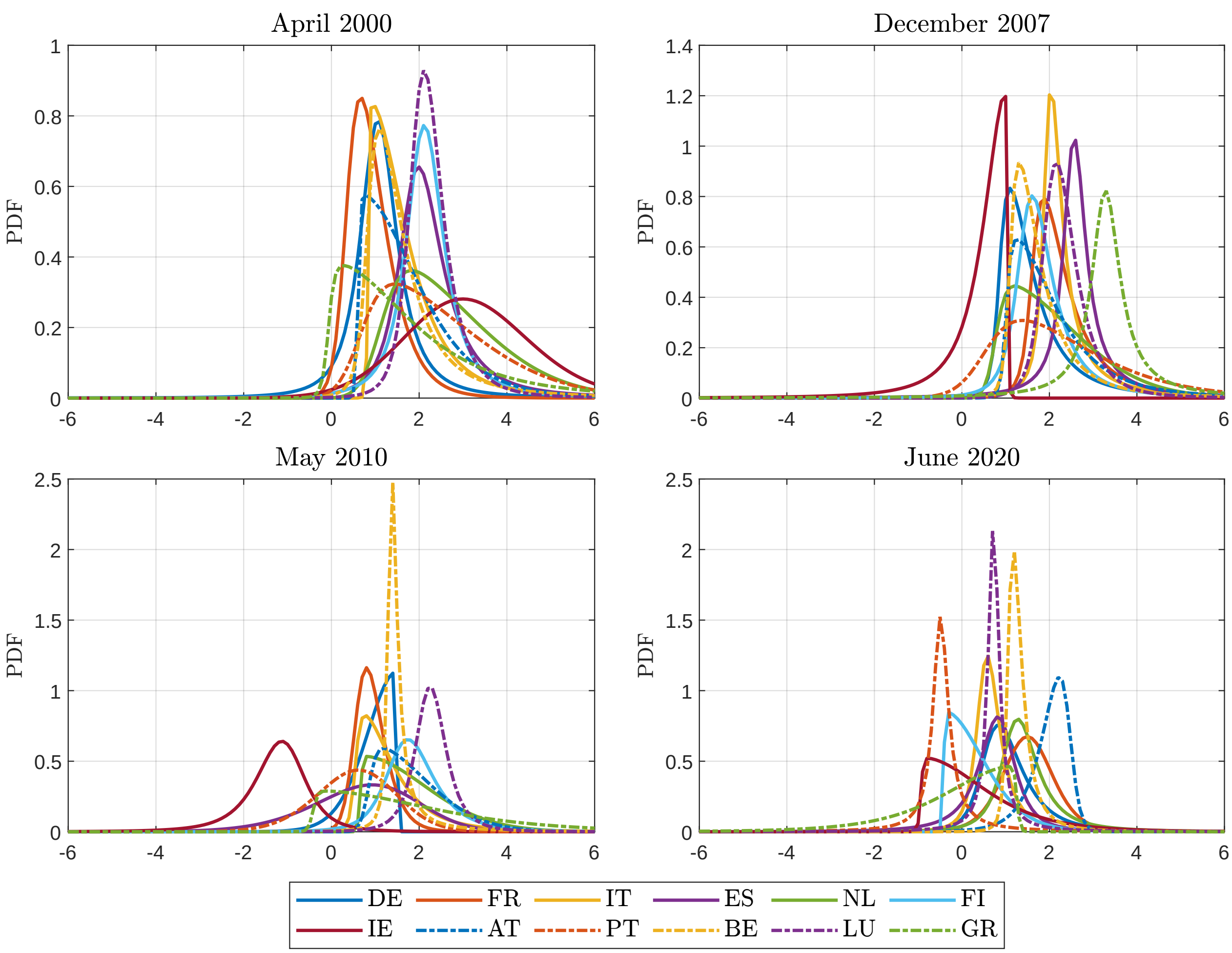
As an illustration, Figure 4 plots the fitted conditional probability density functions of country-specific inflation for four sample dates at different points of the business cycle: April 2000, during the dotcom bubble burst; December 2007, which represented the end of the ECB's tightening cycle before the financial crisis; May 2010, when the Greece received its first bailout; and June 2020, which is the COVID-19 period.

When comparing the conditional densities among different countries on a specific date, notable variations are observed in these densities. These differences stem not only from changes in the estimated values at the point forecast (at the mode) but also from variations in the upper and lower ends of the distributions. During the period of financial distress, marked by the dotcom bubble in the 2000s, some distributions take on a Gaussian shape and are mostly confined to positive values, while others exhibit smaller expected values, higher variance, and positive skewness.

Similarly, when comparing the conditional densities across four different dates, significant time variations in the entire distributions are observed. These variations, once again, arise from both changes in the point forecast and risks associated with the tails.[11] In December 2007, during the expansion of the business cycle, the predictive inflation distributions are

[11]Figure C1 in the Appendix shows changes over time in the dispersion across countries of the four moments of the skewed t-distribution.

FIGURE 4. One-year Ahead Predictive Densities



Note: The panels in this figure show the estimated skewed t-density functions for one-year-ahead country-specific inflation for four sample dates at different points of the business cycle: April 2000, December 2007, May 2010, and June 2020.

concentrated around the ECB's two percent inflation target. In contrast, during economic slowdowns, like in April 2000, May 2010, or June 2020, the distributions appear considerably more dispersed, with greater variations in the point forecast, larger variance, compared to the more stable distribution observed in December 2007.

To accurately assess the risk of inflation dispersion, it is therefore crucial to consider cross-country differences in the complete distributions of future inflation, rather than focusing solely on the forecast midpoint. In the following section, we introduce a measure that accounts for this aspect.

III.2. **KL divergence.** This section aims to quantify the expected disparity in future inflation among euro area countries by measuring the dissimilarity between all predictive inflation distributions. This comprehensive approach allows us to provide a thorough assessment of the expected divergence between countries, considering not just midpoint forecasts but the full predictive distributions.

More formally, we denote by $\hat{f}_t^{i,h}(\pi^i_{t+1,t+1+h}) = f(\pi^i_{t+1,t+1+h}|x^i_t; \hat{\mu}^i_t, \hat{\sigma}^i_t, \hat{\alpha}^i_t, \hat{\nu}^i_t)$ the estimated conditional skew-t density in country i. We define the average divergence, $D_{KL,t}(h)$, at horizon h as

$$D_{KL,t}(h) = \frac{1}{N(N-1)} \sum_i^N \sum_j^N KL_{i,j,t}(h), \qquad \text{for} \quad i \neq j, \tag{3}$$

where

$$KL_{i,j,t}(h) = \int_{-\infty}^{\infty} \log\left(\frac{\hat{f}_t^{i,h}(\pi)}{\hat{f}_t^{j,h}(\pi)}\right) \hat{f}_t^{i,h}(\pi) d\pi, \tag{4}$$

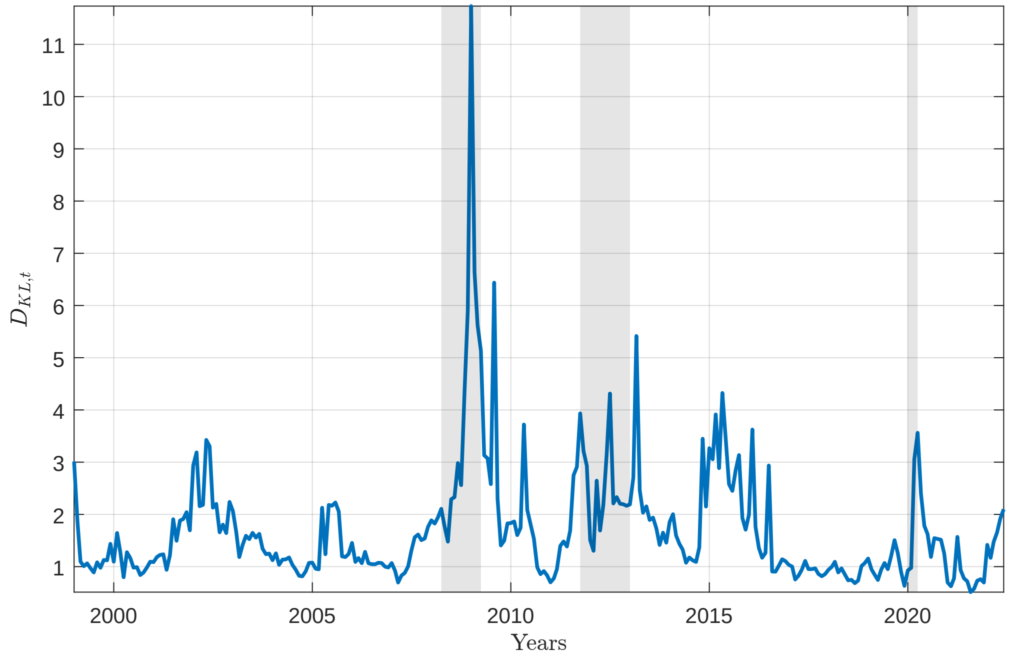
is the KL divergence defined by Kullback and Leibler (1951), which measures the divergence of $\hat{f}_t^{i,h}(\pi)$ from $\hat{f}_t^{j,h}(\pi)$ and where the expectation defined with respect to the density $\hat{f}_t^{i,h}(\pi)$. This measure is always positive and is equal to zero if and only if $\hat{f}_t^{i,h}(\pi) = \hat{f}_t^{j,h}(\pi)$. Intuitively, KL measures the divergence between the conditional density of country i and the conditional density of country j. KL is considered as a good indicator of the correlation degree between two densities. For $N = 2$, the average divergence is fundamentally the divergence in the sense of KL. Our generalized KL divergence to multiple dimensions ($N \geq 2$) follows Sgarro (1981) and takes the average divergence of distributions. Our measure can be interpreted as a sort of "directed distance" between all distributions.

A KL value of zero suggests no risk of inflation dispersion in the euro area, indicating that predicted inflations for each member are identical and drawn from the same predictive distributions. An increase (decrease) in the KL value reflects a divergence (convergence) in the predicted inflation distributions among euro area members, signifying a higher (lower) risk of inflation dispersion. In simpler terms, a greater (lower) KL value implies a higher (lower) likelihood that future realized inflation will vary significantly, based on the current dissimilarity (similarity) in predicted inflation distributions.

Figure 5 depicts our estimated measure of expected divergence in inflation among members of the euro area at horizon $h = 12$, denoted $D_{KL,t}(h = 12)$.[12] Our indicator reveals a clear

[12] In Section D of the Appendix, we generate the term structure of KL divergence to illustrate the evolution of the risk of inflation divergence across various time horizons for $h = 3$ to $h = 24$. The risk of divergence

FIGURE 5. The Risk of Inflation Dispersion $D_{KL,t}(h = 12)$



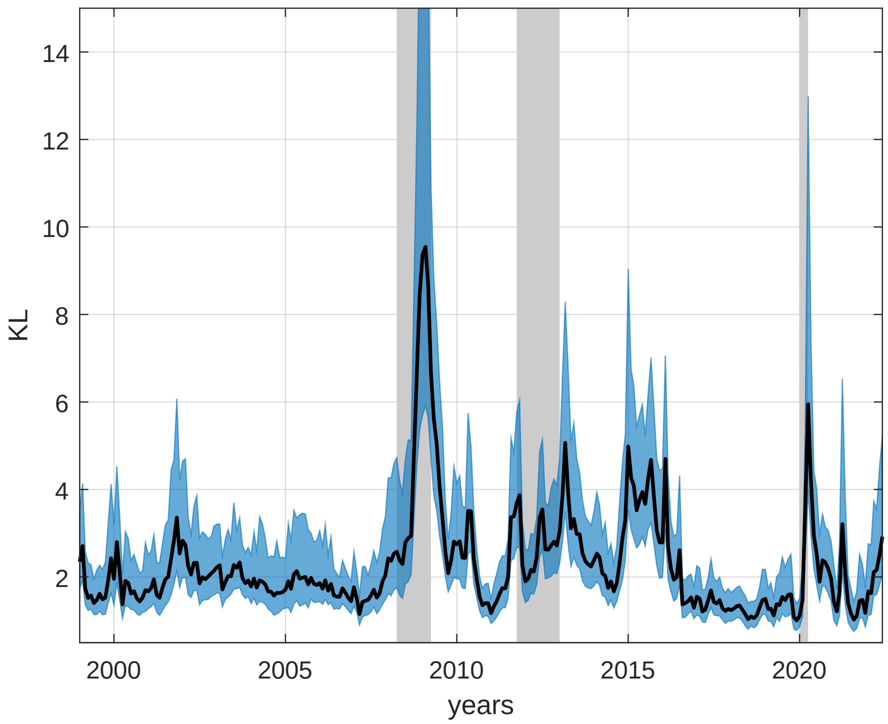
Note: The KL measure $D_{KL,t}(h = 12)$ of one-year-ahead predictive inflation distributions of euro area countries defined by equation (3). Gray shaded areas indicate CEPR-dated recessions.

countercyclical pattern, tending to notably escalate during economic downturns. Examples of such downturns include the period from 2000 to 2002, characterized by events like the 9/11 terrorist attacks, the Dot-com bubble, and corporate scandals, the Great Recession in 2008-09, the sovereign debt crisis in 2010-12, and the COVID-19 recession. Notably, the peaks in divergence appear most pronounced during the Great Recession, with KL divergence values nearly doubling those observed during the sovereign debt crisis or the COVID-19 recession. This suggests that financial conditions might serve as the primary driver behind the generation of inflation dispersion risk. We will confirm this intuition in the next section.

III.3. **Accuracy of KL Divergence.** Figure 5 shows large fluctuations of the risk of inflation dispersion in the euro area. The question nevertheless arises as to the significance of these changes, and in particular of the sharp jumps observed. To address this issue, we compute the distribution of $D_{KL,t}(h)$ given the distributions of coefficients $\hat{\beta}_t^i$ estimated by equation (2). The distributions of $\hat{\beta}_t^i$ are computed in Section B of the Appendix by applying the block-by-block bootstrap developed in Kilian and Kim (2011). For each draw of the

seems to exhibit a steady increase in the near and medium term: its average over the sample period reaches its peak at eighteen-month horizon before declining.

FIGURE 6. The Risk of Inflation Dispersion: Uncertainty



Note: The figure shows the distribution KL divergence $D_{KL,t}(h)$ at horizons $h = 12$ over the sample period based on block-by-block bootstrap developed in Kilian and Kim (2011) (500 draws). Black line represents the median of the distribution and blue shaded areas indicate 68% confidence intervals.

coefficients $\hat{\beta}_t^i$, we calculate the conditional inflation quantile $\hat{Q}_\tau(\pi^i_{t+1,t+1+h}|x^i_t)$, using equation (1) given the set of explanatory variables x^i_t, then fit the skew-t distribution $\hat{f}_t^{i,h}(.)$ and compute the KL divergence series $D_{KL,t}(h)$ using equation (3) specific to this draw. To limit the time taken to calculate this distribution, we use 500 of the 10,000 draws made in Section B .

Figure 6 shows the median and 68% confidence intervals of the KL divergence. First, the median is slightly lower than the estimates shown in Figure 5, suggesting that the distribution of $D_{KL,t}(h)$ is not normal. Second, and more importantly for our purpose, the confidence interval is rather narrow. When the KL divergence peaks, the lower limit of its interval is well above the upper limit of the intervals before and after these peaks. This leads us to conclude that changes in the risk of inflation dispersion in the euro area, as described by our measure, are meaningful and significant.

IV. Anatomy of Risk

In this section, we examine the sources contributing to the risk of increasing inflation divergence along three dimensions: quantile, economic factor, and country.

IV.1. **KL divergence across quantiles.** The KL measure used in this paper takes advantages of the entire predictive inflation distributions to measure the expected inflation divergence between euro area countries. In this section, we investigate whether the divergence is due to differences in the probability masses that the conditional distributions assign to specific range of quantiles of the distributions.

We define the average divergence between quantiles τ and $\tau+10$, $D^{[\tau,\tau+10]}_{KL,t}(h)$, as

$$D^{[\tau,\tau+10]}_{KL,t}(h) = \frac{1}{N(N-1)}\sum_{i}^{N}\sum_{j}^{N} KL^{[\tau,\tau+10]}_{i,j}(h), \qquad \text{for} \quad i \neq j, \tag{5}$$

where

$$KL^{[\tau,\tau+10]}_{i,j,t}(h) = \int_{\pi^i_t(\tau)}^{\pi^i_t(\tau+10)} \log\left(\frac{\hat{f}^{i,h}_t(\pi)}{\hat{f}^{j,t}_t(\pi)}\right)\hat{f}^{i,h}_t(\pi)d\pi, \tag{6}$$

We use the inverse of the cumulative distribution to get the level of inflation $\pi^i_t(\tau)$ in country i at time t associated to the τ-th quantile of $\hat{F}^{i,h}_t(\pi)$, the cumulative distribution associated with $\hat{f}^{i,t}_t(\pi)$.

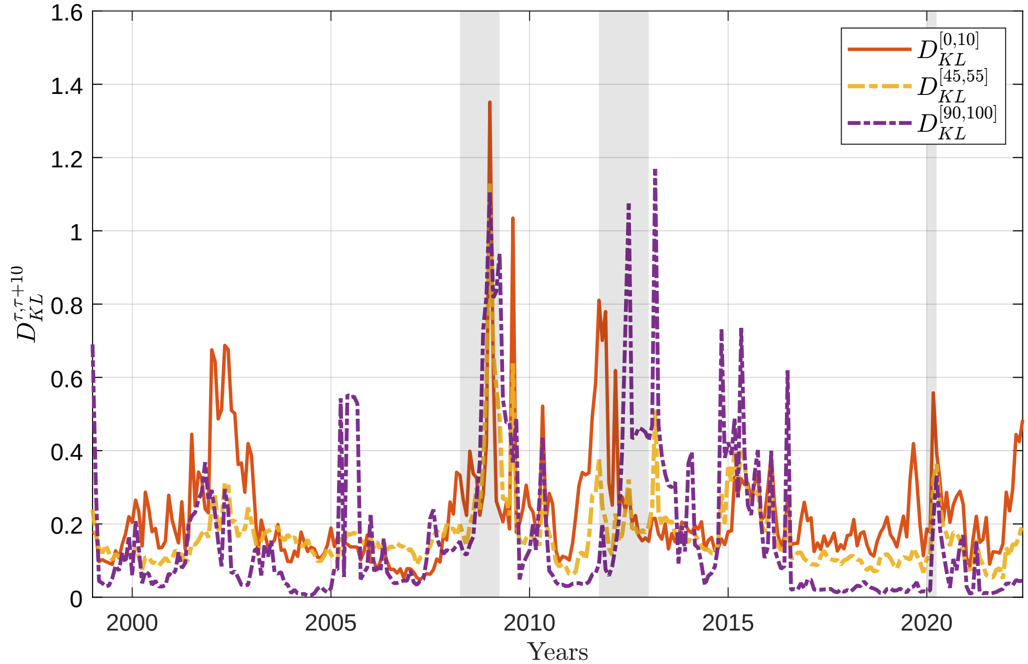
Table I reports the mean and the standard deviation of KL by quantiles $[\tau,\tau+10]$. As can be seen, the risk of inflation dispersion stems more from variations in the left tails of predictive inflation distributions than from variations in the right tails. Notably, the mean of the 10$^{\text{th}}$ quantile is 50% higher that of the 90$^{\text{th}}$ quantile. Interestingly, the standard deviation is higher for KL measures at the tails of the distribution, namely $D^{[0,10]}_{KL,t}$ and $D^{[90,100]}_{KL,t}$. Although these statistics may mask disparities over time, they are nevertheless useful for providing information on the key role of tails in the evolution of our baseline KL measure.

Table I. Mean and standard deviation of $D^{[\tau,\tau+10]}_{KL,t}$ by quantiles $[\tau,\tau+10]$

	Quantiles $[\tau,\tau+10]$									
	$[0,10]$	$[10,20]$	$[20,30]$	$[30,40]$	$[40,50]$	$[50,60]$	$[60,70]$	$[70,80]$	$[80,90]$	$[90,100]$
Mean	0.23	0.20	0.20	0.19	0.18	0.16	0.15	0.13	0.12	0.16
Std. Dev.	0.16	0.12	0.11	0.11	0.10	0.11	0.12	0.13	0.15	0.21

Note: The table shows the mean and standard deviation of $D^{[\tau,\tau+10]}_{KL,t}(h=12)$ defined by equation (5) for quantiles $\tau = 0, 10, \ldots, 90$ over the sample period.

FIGURE 7. The Risk of Inflation Dispersion by Quantile



Note: The figure shows the evolution of KL divergence $D_{KL,t}^{[\tau,\tau+10]}(h = 12)$ for quantiles $\tau = 0$, 45, and 90 defined by equation (5) over the sample period. Gray shaded areas indicate CEPR-dated recessions.

The gap between KL measures by quantile is illustrated by Figure 7, which depicts the time series of quantile-based measures. Two main observations emerge. First, while the 10^{th} quantile is, on average, higher than other quantiles, specific periods exist during which other quantiles exhibit a higher risk of dispersion. For instance, during the sovereign debt crisis, $D_{KL,t}^{[90,100]}$ rose dramatically, whereas $D_{KL,t}^{[0,10]}$ remained at moderated levels. Second, our baseline measure contains information not captured by a simple divergence measure that focuses solely around point forecasts, such as $D_{KL,t}^{[45,55]}$, overlooking cross-country differences in uncertainty and tail risks. For example, during the early 2000s, $D_{KL,t}^{[0,10]}$ and $D_{KL,t}^{[90,100]}$ rapidly rose while $D_{KL,t}^{[45,55]}$ remained relatively stable. Therefore, neglecting cross-country differences in uncertainty and tail risks may distort the inference of the risk of inflation divergence between euro area countries.

IV.2. **KL divergence across drivers.** To gain an appreciation of the economic origins of the risk of inflation divergence described in the previous section, we investigate the role of inflation drivers contained in our Phillips curves. To do so, we proceed as follows. Let us consider one of the variables $j = 1, ..., J$ introduced as a driver of inflation in the quantile regression defined by equation (1). Since the regression is linear, we can rewrite equation (1) as follows:

$$\hat{Q}_\tau(\bar{\pi}^i_{t+1,t+h}|x^i_t) = x^i_{t,j}\hat{\beta}^i_{\tau,j} + \hat{Q}_{\tau,-j}(\bar{\pi}^i_{t+1,t+h}|x^i_t), \tag{7}$$

with

$$\hat{Q}_{\tau,-j}(\bar{\pi}^i_{t+1,t+h}|x^i_t) = x^i_{t,-j}\hat{\beta}^i_{\tau,-j}, \tag{8}$$

where j stands for the $j-$element and $(-j)$ for the exclusion of the $j-$element from the set of J variables. Therefore, the first term in the right-hand side of equation (7) measures the contribution of variable j to the quantile of future inflation and the second one the contribution of the other variables, defined by equation (8).

Using this decomposition, we compare KL measures $D_{KL,t,-j}(h)$ based on $\hat{Q}_{\tau,-j}(\bar{\pi}^i_{t+1,t+h}|x^i_t)$, that is the quantile predicted without variable j, to our benchmark measure $D_{KL,t}(h)$, based on $\hat{Q}_\tau(\bar{\pi}^i_{t+1,t+h}|x^i_t)$, when all variables are taken into account. $D_{KL,t,-j}(h) < D_{KL,t}(h)$ means that the driver j is a source of divergence since the KL is lower when the driver j is not taken into when measuring divergence. Conversely, if $D_{KL,t,-j}(h) > D_{KL,t}(h)$, the driver j is then a source of convergence since the KL is higher when the driver j is not taken into account when measuring divergence.

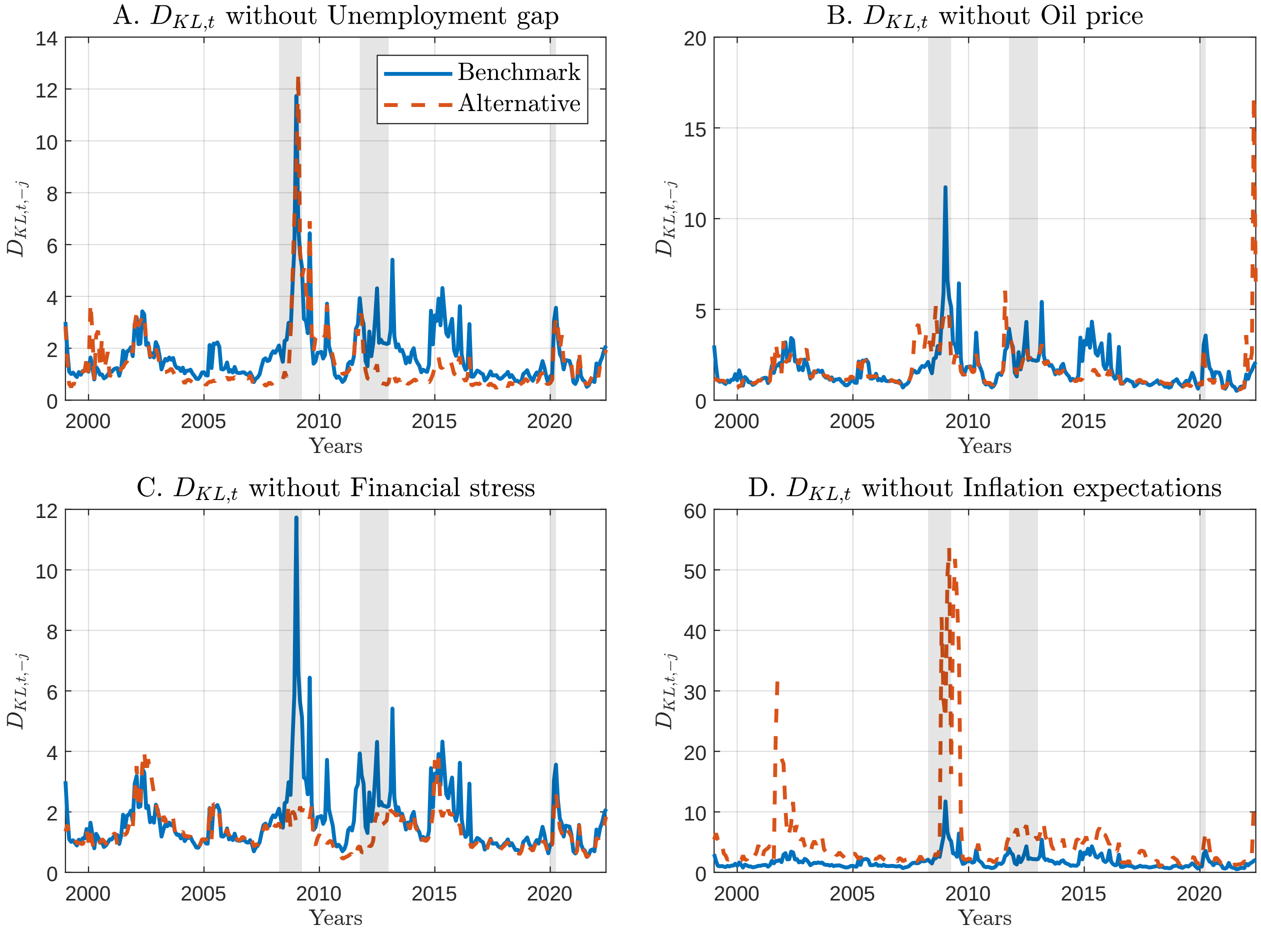
Figure 8 compares the KL statistics $D_{KL,t,-j}$ for four inflation drivers.[13] Panel A shows that unemployment plays a substantial role in inflation divergence, especially in the aftermath of the sovereign debt crisis. Before 2012, the two lines are indeed very close.

Panel B shows that the gap between KL statistics is almost close to zero during the first decade of the period. Interestingly, in the last period oil price is a source of reduction of the risk of inflation dispersion: the KL without oil price skyrockets at the end of period. This is quite logical since all countries have been hit by the global energy crisis at the end of the sample. So even if in average, oil price is minor source of inflation dispersion risk it can be punctually a source of divergence or convergence of inflation in the euro area.

Panel C shows that financial stress is a key source of inflation risk in the euro area. The KL without financial indicator is substantially lower during the period 2008-2015 of financial turbulences (the dashed red line is below the solid blue one). Apart this episode, financial conditions do not drive the risk of inflation divergence in the euro area.

[13] So, four of the six variables considered in the Phillips curve. We do not consider the KL when the constant and past inflation are removed.

Figure 8. The Risk of Inflation Dispersion by Inflation Driver

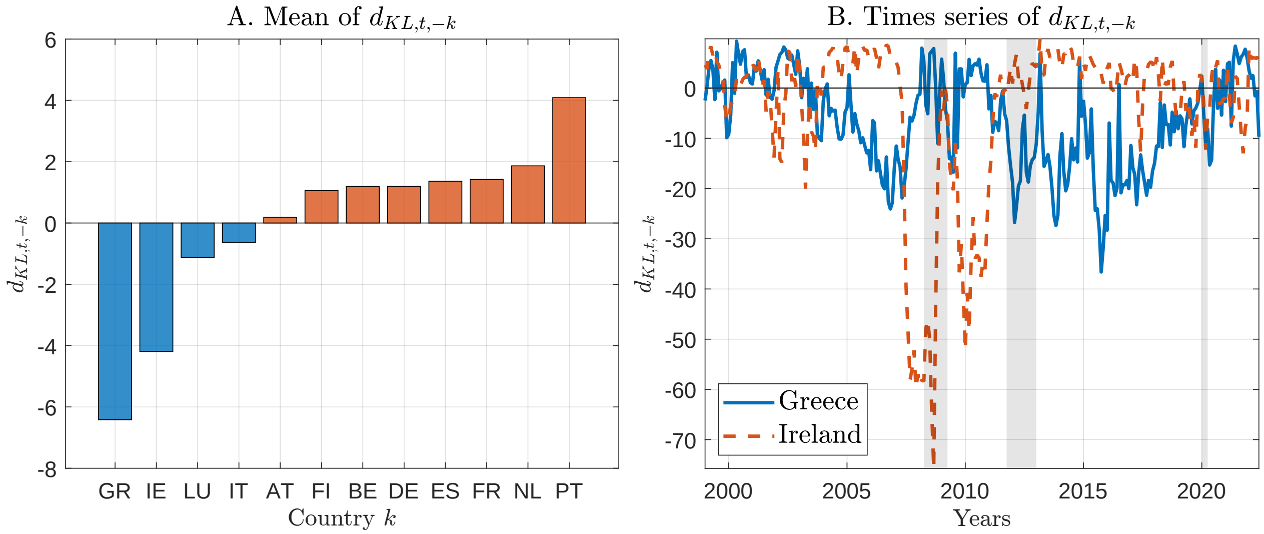


Note: The figure compares the benchmark KL statistic $D_{KL,t}(h = 12)$ to the alternative KL statistics $D_{KL,t,-j}(h = 12)$ when inflation driver j is removed for j=[Unemployment gap, Oil price, Financial stress, Inflation expectations]. Gray shaded areas indicate CEPR-dated recessions.

Finally, Panel D shows that inflation expectations are a key source of inflation convergence in the euro area. When inflation expectation is removed from the inflation drivers, the KL statistic skyrockets several times to values above 20. This demonstrates the importance of anchoring expectations, which makes converge inflation forecasts between countries and thus limits the risk of inflation dispersion in the euro area.

IV.3. **KL divergence across countries.** To conclude this section on the characteristic of the risk of inflation dispersion, we assess the role of each country in the divergence of predictive distributions. We recompute the KL measure for eleven countries by sequentially removing each of the twelve countries. In practical terms, we compute the divergence,

Figure 9. The Risk of Inflation Dispersion by Country



Note: Panel A reports the mean values of $d_{KL,t,-k}(h = 12)$, defined by equation (10), for each country k over the sample period: $\bar{d}_{KL,-k}(h = 12) = (1/T) \times \sum_{t=1}^{T} d_{KL,t,-k}(h = 12)$. X-axis indicates country k. Countries are ranked in ascending order. Panel B shows the values of $d_{KL,t,-k}(h = 12)$, defined by equation (10) for countries k=[Greece, Ireland] over the sample period. Gray shaded areas indicate CEPR-dated recessions.

$D_{KL,t,-k}(h)$, at horizon h without country k as

$$D_{KL,t,-k}(h) = \frac{1}{(N-1)[(N-1)-1]} \sum_{i}^{N-1} \sum_{j}^{N-1} KL_{i,j,t}(h) \tag{9}$$

for $i \neq j$, $i \neq k$, $j \neq k$ and $k = 1, ..., N$, where $KL_{i,j,t}(h)$ is still defined by equation (4). The difference with respect to $D_{KL,t}(h)$, defined by equation (3), is that the k-country is not considered to compute $D_{KL,t,-k}(h)$ which therefore measures the divergence between all countries apart k. To measure the role of country k in the divergence of inflation risks, we compute the deviation in percentage between the two KL statistics as follows:

$$d_{KL,t,-k}(h) = 100 \times \frac{D_{KL,t,-k}(h) - D_{KL,t}(h)}{D_{KL,t}(h)}. \tag{10}$$

If $d_{KL,t,-k}(h)$ is negative, it means that the country k is a source of divergence to the extent that the KL is lower without the country k than when this country is included to compute the KL. Conversely, a positive $d_{KL,t,-k}(h)$ means that the country k is a source of convergence to the extent that the KL is higher without country k than when this country is included to compute the KL.

Panel A of Figure 9 reports the mean values of $d_{KL,t,-k}$ for each country k over the sample period. Four countries are source of divergence of inflation risks (namely Greece, Ireland, Luxembourg, Italy) and eight countries are source of convergence. It is important to note that our proposed measure of inflation risk dispersion is not determined by a single marginal country. If we consider the two extreme cases, KL variations are relatively modest: removing Greece from the sample reduces dispersion by 6%, while excluding Portugal increases it by 4%. No single country is the only source of dispersion in the euro area on average over the period. This result does not mean that there are not periods when certain countries play a dominant role in the risk of inflation dispersion, especially during financial crisis.

Panel B of Figure 9 reports the values of $D_{KL,t,-k}$ for the two main contributors to divergence, namely Greece and Ireland, over the sample period (Figure E1 in the Appendix reports the values for all countries). The role of Ireland as a source of divergence is concentrated during the years of the Great Recession, but with a huge impact. Without Ireland, the KL statistics are more than divided by two. Greece has contributed to the risk of divergence in the euro area during the years before the Great Recession and in almost all the second decade of the euro area, in the aftermath of the sovereign debt crisis.

V. Monetary Policy Implications

This section investigates whether the risk of inflation dispersion matters for the transmission of monetary policy. In particular, we examine the conditional responses of both output and prices to a monetary policy shock when the risk of inflation dispersion is high or low. We do so by estimating simple local projections as proposed by Jordà (2005) with an identified instrument for monetary policy. In particular, we use the monetary policy surprises introduced by Jarociński and Karadi (2020), denoted MP_t, as an instrument. Those are high-frequency financial market surprises at monetary policy announcements adjusted for central bank information effects using poor-man's sign restriction.[14]

We denote as x_t the vector of controls, which includes three lags of macroeconomic and financial variables, namely German one-year government bond yield, industrial production, HICP prices, BBB bond spread, and EURO STOXX 50.[15] We interact the monetary surprises

[14]This restriction involves setting the monetary surprise to zero in cases where stock returns on announcement days move in the same direction as the surprise in the market interest rate.

[15]Where appropriate, we take first difference or log first difference transformations of the data.

series with our measure of risk, $D_{KL,t}$, described previously. Consider the following set of local projections relating future outcome of interest, y_{t+h} at horizon h, to exogenous variation in monetary policy today:

$$y_{t+h} = \alpha_h + MP_t\beta_h + (D_{KL,t} \times MP_t)\gamma_h + D_{KL,t}\delta_h + x_t\phi_h + \nu_{t+h}, \tag{11}$$

for $h = 0, \ldots, H-1$ and $t = 1, \ldots, T$.

Equation (11) is estimated from the first quarter of 1999 to the fourth quarter of 2019 using OLS. We do not include the Covid period due to unprecedented variation in our macroeconomic variables, causing severe distortion in parameter estimates. We compute standard errors that are robust against heteroskedasticity. The total effect of monetary policy shock at horizon h is obtained by summing up the linear and nonlinear terms as follows:

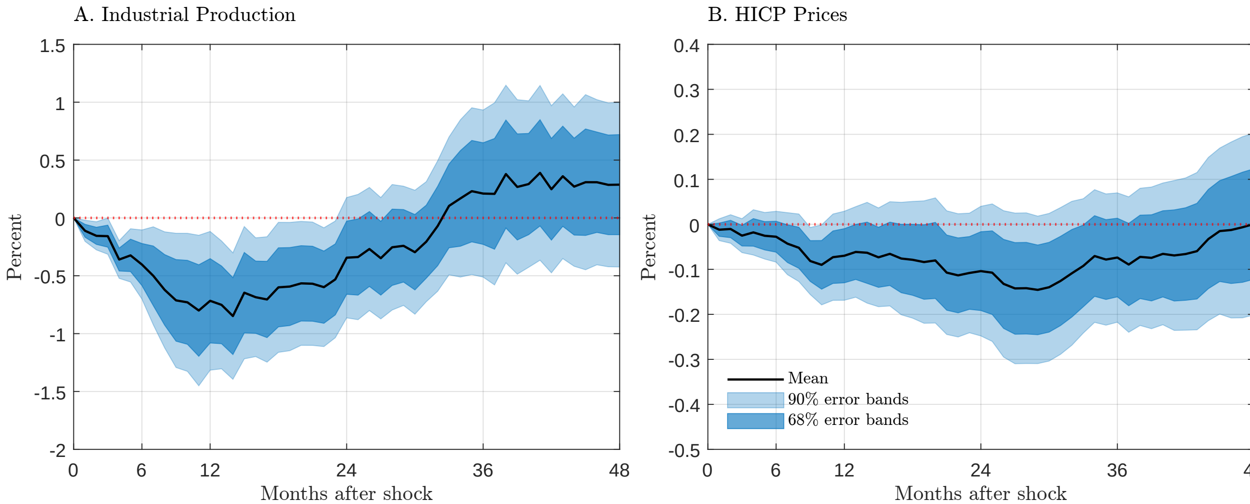
$$IRF_h(D_{KL,t}) = \beta_h + D_{KL,t}\delta_h. \tag{12}$$

Thus, the total response defined in equation (12) depends potentially on the degree of risk of inflation dispersion.

To check the consistency of our specification, we begin by showing estimates of the total effect of a monetary policy shock at horizon h when the risk of inflation dispersion is at its median level of the historical sample. Figure 10 shows the effects on industrial production and HICP prices following an one standard deviation increase in the monetary policy shock. As expected, a monetary policy tightening provides a substantial short- and medium-run contraction in both output and prices. Both variables immediately decline and then steadily return to their pre-shock levels. The maximum impact is -0.75 percent on industrial production and -0.15 percent on prices. The response of prices appears much more persistent, which is consistent with the literature.

The main result of this Section lies in Figure 11, which reports the impulse responses of industrial production (Panel A) and prices (Panel B) for two given values of $D_{KL,t}$, namely its values at 10th and 90th percentiles. We find that the transmission of monetary policy does depend on the degree of risk of inflation dispersion. A one-standard deviation in the unanticipated increase in the policy surprises, conditional on a low risk of inflation dispersion (Panel A.1), leads to a peak drop on output of around 1.00 percent after one year. In contrast, the effect of monetary policy on output when the risk of inflation dispersion is

FIGURE 10. Impulse Responses to a Monetary Policy Shock when the Risk is at its Median Level



Note: The size of the shock is scaled to induce an immediate one standard deviation increase in the shock. In each panel, the median is reported in solid line, while the 68% and 90% error bands are shown by blue areas.

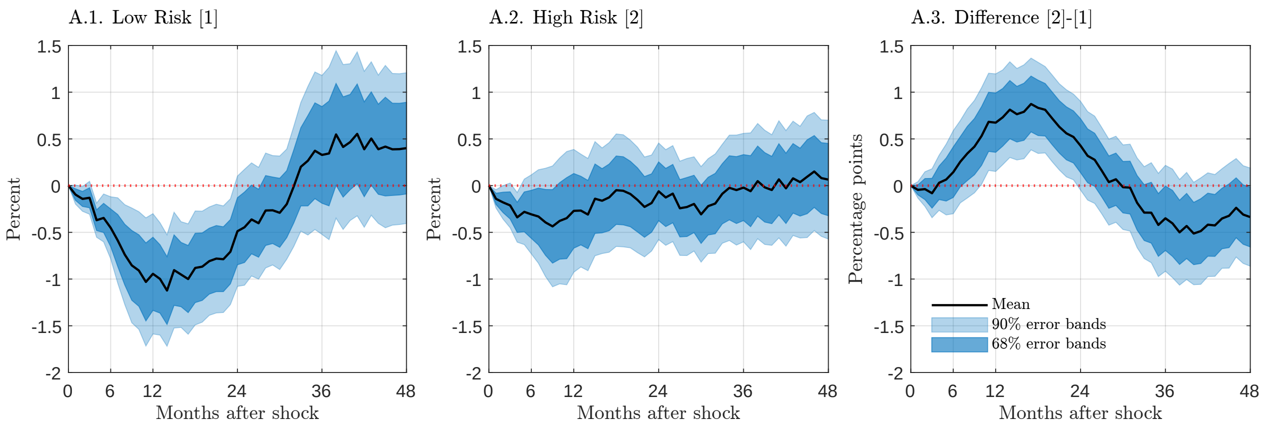
high is mitigated (Panel A.2). Output falls until reaching its minimum of about −0.50 percent after six months (at this point, the impact is more than twice smaller than in the low risk regime). These differences appear to be significant when taking into account confidence intervals (Panel A.3); both 68% and 90% error bands lie exclusively within the positive region between the first and second years after the initial shock.

Similarly, the response of prices appears to be much larger when the risk of inflation dispersion is low (Panel B.1). Indeed, the maximum response is approximately −0.2 percent. By contrast, the effects appear to be non-significantly different from zero when this risk is high (Panel B.2). The differences in impulse reponses are statistically significant (Panel B.3) as they lie exclusively within the positive region for several months after the shock.

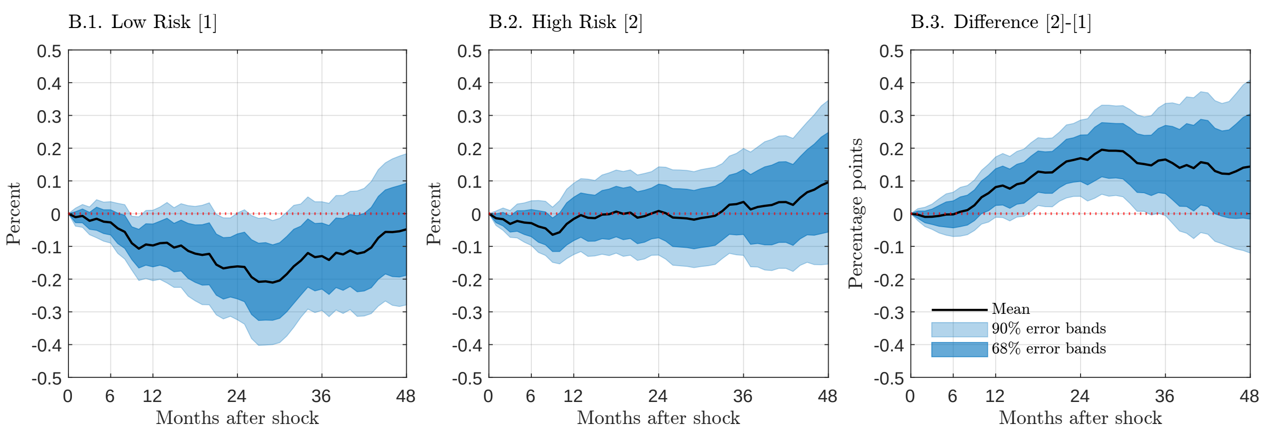
To sum up, our results suggest that the risk of inflation dispersion tends to weaken the macroeconomic impact of monetary policy, both on output and prices. In a certain way, our results align with the recent work of Dong et al. (2024), which show that household inflation disagreement weakens the effects of monetary policy on consumption and inflation. According to their mechanism, households with higher inflation expectations perceive lower real interest rates, prompting them to borrow more aggressively until they hit borrowing constraints. Once constrained, their ability to adjust consumption in response to monetary

FIGURE 11. Impulse Responses to a Monetary Policy Shock when the Risk is Low or High

(A) Industrial Production



(B) HICP Prices



Note: The size of the shock is scaled to induce an immediate one standard deviation increase in the shock. In each panel, the median is reported in solid line, while the 68% and 90% error bands are shown by blue areas.

policy changes is limited. As inflation disagreement increases, a larger proportion of households become borrowing-constrained, thereby weakening the impact of monetary policy. A similar mechanism may operate at the cross-country level: when inflation expectations vary significantly across member states, a single monetary policy stance results in diverging real interest rates across economies, leading to heterogeneous and overall weaker policy transmission because some countries' consumers and firms may hit borrowing constraints earlier. Thus, inflation expectation dispersion across countries may similarly impair the transmission of monetary policy. Cleary, our empirical evidence supports this view.

VI. Conclusion

We introduced a comprehensive methodology for measuring the risk of inflation dispersion among euro area countries over time. The approach considered the degree of dissimilarity in predictive inflation distributions among euro area countries. By doing so, it addressed not only cross-countries differences in point forecasts of inflation, but also cross-countries differences in uncertainty and tail risks. Based on our measure, we documented that the rising risk of inflation dispersion is mainly driven by a deterioration in financial conditions, while a robust anchoring of inflation expectations in each country tends to mitigate this risk. Finally, we demonstrated that monetary policy loses effectiveness when dispersion risk is high: a contractionary monetary policy shock has only half the impact on output and prices compared to periods of low risk.

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APPENDIX: THE RISK OF INFLATION DISPERSION IN THE EURO AREA

STÉPHANE LHUISSIER, AYMERIC ORTMANS AND FABIEN TRIPIER

This Appendix consists of the following sections:

Appendix A. Data

All variables are monthly time series covering January 1999 through July 2023. The following variables use data obtained directly from different sources:

- Harmonized Index of Consumer Prices
  - Source: ECB - ICP (Indices of Consumer prices). Details: Monthly – Neither seasonally nor working day adjusted – HICP - All-items excluding energy and food – Eurostat – Index
  - Data transformation: Authors' calculations using the x13 toolbox to get seasonally adjusted series for each euro area member countries.
- Unemployment rate
  - Source: Eurostat - Unemployment by sex and age – monthly data. Details: Monthly – Seasonally adjusted data, not calendar adjusted data – Total – Percentage of population in the labor force
- Natural Rate of Unemployment
  - Source: European Commission (AMECO). Details: NAWRU
  - Data transformation: linear interpolation
- Oil Prices
  - Source: U.S. Energy Information Administration - Spot Prices. Details: Crude Oil Prices: Brent - Europe - Dollars per Barrel, Not Seasonally Adjusted
- Financial conditions (CISS)
  - Source: ECB - CISS. Details: Daily – ECB – Economic indicator – New Composite Indicator of Systemic Stress (CISS) – Index
  - Data transformation: Authors' calculations to get monthly average of the series.
- Financial conditions (CLIFS)
  - Source: ECB - CLIFS. Details: Monthly – ECB – Economic indicator – Country-Level Index of Financial Stress (CLIFS) Composite Indicator – Index
- Long-Term Inflation Expectations
  - Source: Consensus Economics. Details: Six-to-ten-years-ahead mean CPI inflation forecasts.
  - Data transformation: Euro area forecasts for Luxembourg (no forecast available), spline interpolation for all missing data in April 1999.

Appendix B. National Phillips Curve Estimates (tables)

This section presents the results of the quantile Phillips curve estimates by country. The results are displayed in Tables B1 to B3. Each table reports the estimated coefficients of equation (2) for each country for quantiles $\tau = \{10, 50, 90\}$, respectively. The last two rows of the tables report the unweighted means and the standard deviations of coefficients across countries.

First of all, the mean and the standard deviation of coefficient λ_τ^i associated to long-term inflation expectations across countries remain relatively stable over the 10^{th} and the 50^{th} quantiles (around 0.64 and 0.68, respectively). However, the mean of the coefficient becomes lower at the top of the distribution (90^{th}) at around 0.45. Overall, the average weight of inflation expectations is greater than that of past inflation for the 10^{th} and 50^{th} quantiles, but is lower at the top of the distribution. This result is in line with Baba et al. (2023) who also find that inflation has become increasingly backward looking across Europe since the COVID pandemic. Our results also reveal that inflation anchoring is not the same when looking at the weight of inflation expectations country-by-country.

Focusing on the θ_τ^i coefficient (i.e., the slope of the Phillips curve), the magnitude of the cross-sectional mean is twice higher for the 50^{th} and 90^{th} quantiles than for the 10^{th} quantile. Unemployment seems to affect inflation much more in the middle or at the top of the distribution than at the bottom in the euro area, on average. This result suggests that labor market conditions matter more for upside risks to inflation than for downside inflation risks. Such nonlinearities in the relationship between slack and inflation corroborate those from Gagnon and Collins (2019) in which the Phillips curve is normally steep but becomes nonlinear only when inflation is low.

The cross-sectional mean of the coefficient associated with financial stress, δ_τ^i, is strongly negative and higher in the upper tail (although stable across quantiles). Although surprising, this result is consistent with the role of tighter financial conditions in the occurrence of low inflation episodes in the euro area.[16] Our results corroborate a vast literature maintaining that there is a nonlinear relationship between financial sector and macroeconomy depending on the state of the economy. Notable examples include He and Krishnamurthy (2012, 2013)

[16] Lopez-Salido and Loria (2024) also find that the tails of euro area inflation predictive distribution are equally negatively affected by tighter financial conditions, contrasting with their main finding using U.S. data.

and Brunnermeier and Sannikov (2014) for the theory, and Hubrich and Tetlow (2015) and Lhuissier (2017) for the empirics. The estimated coefficient shows important disparities between euro area countries.

Finally, the cross-sectional mean of the γ_τ^i coefficient is much higher for the 90$^{\text{th}}$ than for the 10$^{\text{th}}$ quantile, suggesting that oil price affects upside risks to inflation relatively more than downside inflation risks (1.46 against 0.46).

As a whole, estimated national Phillips curve results show important non-linearities across quantiles. Moreover, it is worth noting that the non-linearities across quantiles are not the same for all countries, providing grounds for looking at the dispersion of conditional quantiles across euro area countries.

Table B1. Phillips Curve Estimates for the 10$^{\text{th}}$ Quantile

	$\hat{\mu}_\tau^i$	$\hat{\lambda}_\tau^i$	$\hat{\theta}_\tau^i$	$\hat{\gamma}_\tau^i$	$\hat{\delta}_\tau^i$
Germany	−1.12	0.47	−0.00	0.39	0.55
	[−1.27;−0.98]	[0.21;0.73]	[−0.14;0.14]	[0.16;0.62]	[0.09;1.01]
France	−0.67	0.51	−0.23	0.21	−0.97
	[−0.85;−0.50]	[0.30;0.73]	[−0.34;−0.12]	[−0.03;0.45]	[−1.52;−0.41]
Italy	−0.49	0.33	−0.12	−0.18	−1.26
	[−0.61;−0.37]	[0.22;0.45]	[−0.17;−0.08]	[−0.41;0.05]	[−1.72;−0.80]
Spain	−0.75	0.71	−0.09	0.20	−2.80
	[−1.14;−0.36]	[0.43;0.98]	[−0.14;−0.04]	[−0.41;0.82]	[−4.39;−1.21]
Netherlands	−1.09	0.91	−0.21	0.62	0.16
	[−1.30;−0.87]	[0.81;1.00]	[−0.35;−0.07]	[0.36;0.89]	[−0.47;0.80]
Finland	−0.86	0.50	−0.29	0.70	1.02
	[−1.03;−0.68]	[0.33;0.68]	[−0.40;−0.18]	[0.39;1.02]	[0.32;1.73]
Ireland	−1.43	0.56	0.35	0.67	−3.36
	[−1.66;−1.20]	[0.39;0.72]	[0.14;0.57]	[0.10;1.23]	[−5.36;−1.35]
Austria	−0.56	0.75	0.06	−0.06	−0.27
	[−0.68;−0.44]	[0.58;0.91]	[−0.09;0.21]	[−0.29;0.17]	[−0.83;0.29]
Portugal	−1.32	0.53	0.13	0.62	−1.00
	[−1.60;−1.03]	[0.39;0.68]	[0.02;0.25]	[0.03;1.21]	[−1.89;−0.11]
Belgium	−0.76	0.97	−0.05	0.30	−0.13
	[−0.84;−0.68]	[0.84;1.11]	[−0.12;0.03]	[0.14;0.46]	[−0.48;0.21]
Luxembourg	−0.75	0.42	−0.20	0.68	1.06
	[−0.92;−0.57]	[0.15;0.69]	[−0.43;0.03]	[0.54;0.81]	[0.44;1.68]
Greece	−0.47	1.00	−0.16	1.40	−5.26
	[−1.19;0.25]	[0.91;1.09]	[−0.21;−0.10]	[0.74;2.05]	[−7.80;−2.73]
Mean	-0.85	0.64	-0.07	0.46	-1.02
Std. Dev.	0.32	0.22	0.18	0.42	1.92

Note: Coefficients of the quantile Phillips curve defined by equation (2) estimated by country for the 10$^{\text{th}}$ quantile. The last two rows show the unweighted means and the standard deviations of coefficients across countries. 68% confidence intervals are in brackets and are based on block-by-block bootstrap (10,000 draws) developed in Kilian and Kim (2011).

Table B2. Phillips Curve Estimates for the 50th Quantile

	$\hat{\mu}^i_\tau$	$\hat{\lambda}^i_\tau$	$\hat{\theta}^i_\tau$	$\hat{\gamma}^i_\tau$	$\hat{\delta}^i_\tau$
Germany	−0.46 [−0.66;−0.27]	0.92 [0.63;1.21]	−0.07 [−0.29;0.15]	0.38 [0.10;0.67]	−0.30 [−0.70;0.10]
France	−0.24 [−0.35;−0.13]	0.78 [0.58;0.97]	−0.38 [−0.50;−0.27]	0.06 [−0.12;0.24]	−1.20 [−1.65;−0.76]
Italy	−0.02 [−0.18;0.14]	0.33 [0.16;0.50]	−0.11 [−0.18;−0.05]	−0.06 [−0.37;0.24]	−1.02 [−1.56;−0.47]
Spain	−0.27 [−0.48;−0.06]	0.76 [0.54;0.99]	−0.06 [−0.12;−0.00]	0.43 [0.06;0.79]	−1.03 [−2.15;0.10]
Netherlands	−0.19 [−0.41;0.03]	0.79 [0.62;0.96]	−0.46 [−0.59;−0.33]	0.83 [0.49;1.17]	−0.42 [−1.83;0.98]
Finland	−0.15 [−0.29;−0.01]	0.32 [0.15;0.48]	−0.20 [−0.34;−0.06]	0.95 [0.70;1.20]	0.49 [−0.31;1.29]
Ireland	−0.09 [−0.40;0.22]	0.37 [0.22;0.52]	0.34 [0.13;0.55]	1.23 [0.89;1.57]	−2.83 [−4.56;−1.11]
Austria	−0.11 [−0.22;0.00]	0.80 [0.50;1.09]	−0.00 [−0.16;0.16]	0.35 [0.04;0.66]	0.28 [−0.56;1.12]
Portugal	−0.23 [−0.56;0.10]	0.52 [0.29;0.75]	−0.01 [−0.22;0.19]	0.74 [0.23;1.24]	−1.38 [−2.61;−0.15]
Belgium	−0.31 [−0.46;−0.17]	0.69 [0.47;0.91]	−0.01 [−0.13;0.10]	0.49 [0.24;0.74]	−0.23 [−0.76;0.30]
Luxembourg	−0.14 [−0.24;−0.03]	0.86 [0.76;0.95]	−0.30 [−0.40;−0.20]	0.67 [0.48;0.86]	0.15 [−0.33;0.62]
Greece	0.85 [0.52;1.17]	1.00 [0.92;1.08]	−0.17 [−0.20;−0.14]	0.77 [0.21;1.32]	−5.17 [−7.91;−2.42]
Mean	-0.11	0.68	-0.12	0.57	-1.06
Std. Dev.	0.32	0.24	0.21	0.37	1.58

Note: Coefficients of the quantile Phillips curve defined by equation (2) estimated by country for the 50th quantile. The last two rows show the unweighted means and the standard deviations of coefficients across countries. 68% confidence intervals are in brackets and are based on block-by-block bootstrap (10,000 draws) developed in Kilian and Kim (2011).

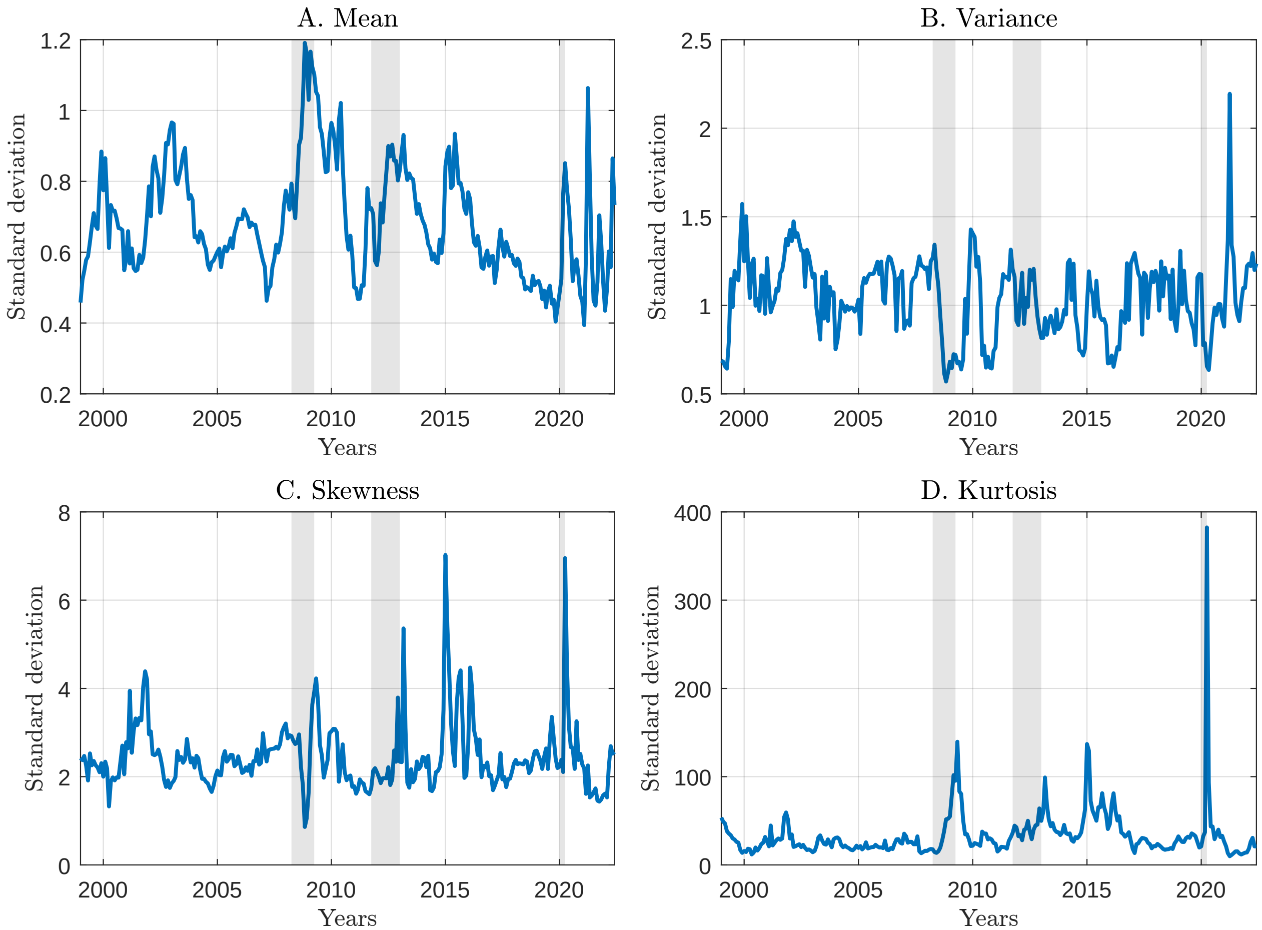
Table B3. Phillips Curve Estimates for the 90th Quantile

	$\hat{\mu}_\tau^i$	$\hat{\lambda}_\tau^i$	$\hat{\theta}_\tau^i$	$\hat{\gamma}_\tau^i$	$\hat{\delta}_\tau^i$
Germany	1.48 [0.85;2.11]	0.00 [−0.42;0.43]	−0.07 [−0.43;0.28]	0.72 [0.12;1.32]	−1.74 [−2.69;−0.80]
France	1.30 [0.75;1.85]	0.30 [−0.07;0.66]	−0.63 [−0.84;−0.43]	0.56 [0.13;0.99]	−2.88 [−4.07;−1.69]
Italy	1.40 [0.94;1.86]	0.50 [0.24;0.75]	−0.40 [−0.62;−0.18]	1.23 [0.48;1.97]	−2.09 [−3.43;−0.76]
Spain	1.00 [0.63;1.37]	0.89 [0.67;1.10]	−0.11 [−0.21;−0.02]	1.49 [0.80;2.18]	−1.05 [−2.69;0.58]
Netherlands	1.57 [0.92;2.22]	0.58 [0.21;0.95]	−0.86 [−1.18;−0.53]	1.97 [1.03;2.92]	−1.71 [−4.46;1.04]
Finland	0.41 [0.13;0.69]	0.66 [0.40;0.92]	0.12 [−0.11;0.34]	1.83 [1.13;2.53]	1.18 [−0.03;2.38]
Ireland	1.78 [1.28;2.29]	0.04 [−0.13;0.22]	0.75 [0.48;1.02]	0.84 [0.25;1.43]	−1.34 [−4.10;1.43]
Austria	1.07 [0.56;1.58]	0.00 [−0.39;0.39]	0.26 [0.01;0.50]	1.98 [1.00;2.97]	0.46 [−0.87;1.78]
Portugal	2.32 [1.65;2.99]	0.49 [0.26;0.73]	−0.32 [−0.60;−0.04]	1.91 [1.10;2.72]	−4.58 [−6.94;−2.22]
Belgium	1.34 [0.81;1.86]	0.00 [−0.40;0.40]	−0.02 [−0.24;0.19]	1.81 [0.91;2.70]	−1.67 [−2.97;−0.37]
Luxembourg	0.41 [0.11;0.71]	0.99 [0.88;1.10]	−0.33 [−0.53;−0.13]	1.42 [0.93;1.92]	0.37 [−0.59;1.34]
Greece	1.43 [0.78;2.08]	0.91 [0.75;1.06]	−0.13 [−0.19;−0.07]	1.78 [0.39;3.17]	0.63 [−2.22;3.48]
Mean	1.29	0.45	-0.15	1.46	-1.20
Std. Dev.	0.53	0.38	0.42	0.51	1.65

Note: Cefficients of the quantile Phillips curve defined by equation (2) estimated by country for the 90th quantile. The last two rows show the unweighted means and the standard deviations of coefficients across countries. 68% confidence intervals are in brackets and are based on block-by-block bootstrap (10,000 draws) developed in Kilian and Kim (2011).

Appendix C. Cross-country Dispersion of Moments

Figure C1. Cross-Country Dispersion of Skewed t-Distribution Moments over Time



Appendix D. Term structure of KL Divergence

We generate the term structure of KL divergence to illustrate the evolution of the risk of inflation divergence across various time horizons. The process involves using quantile regression methods on our dataset consisting of twelve euro area countries to forecast periods ranging from three to twenty-four months. Subsequently, for each horizon and country, we empirically map the quantile regression estimates to the skewed t-distribution. Finally, we compute the average KL divergence for each horizon, representing the term structure of inflation divergence risk.

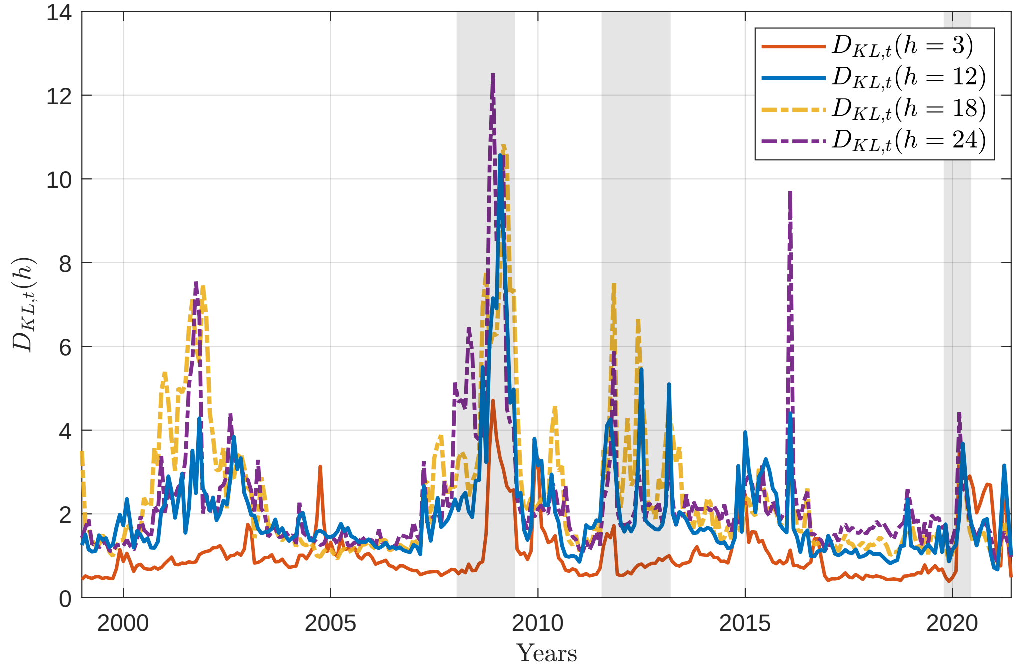
Table D1 displays the mean and the standard deviation of the resulting term structure for projection horizons up to two years. The risk of divergence seems to exhibit a steady increase in the near and medium term: its average over the sample period reaches its peak at eighteen-month horizon before declining. Regarding the standard deviation, KL divergence is increasingly volatile up to a one-year horizon before decreasing thereafter. Medium- and long-term KL divergences (for $h = 18$ or $h = 24$, respectively) appear to be more responsive during economic contractions compared to short-term KL divergence (for $h = 3$), as illustrated in Figure D1.

Table D1. Mean and standard deviation of $D_{KL,t}(h)$ by horizon h

	Horizon h							
	$h = 3$	$h = 6$	$h = 9$	$h = 12$	$h = 15$	$h = 18$	$h = 21$	$h = 24$
Mean	1.04	1.44	1.51	1.97	2.30	2.39	2.39	2.27
Std. Dev.	0.70	0.96	0.83	1.23	1.54	1.67	1.49	1.57

Note: The table shows the mean and standard deviation of $D_{KL,t}(h)$ defined by equation (3) at horizons $h = 3, 6, \ldots, 24$ months over the sample period.

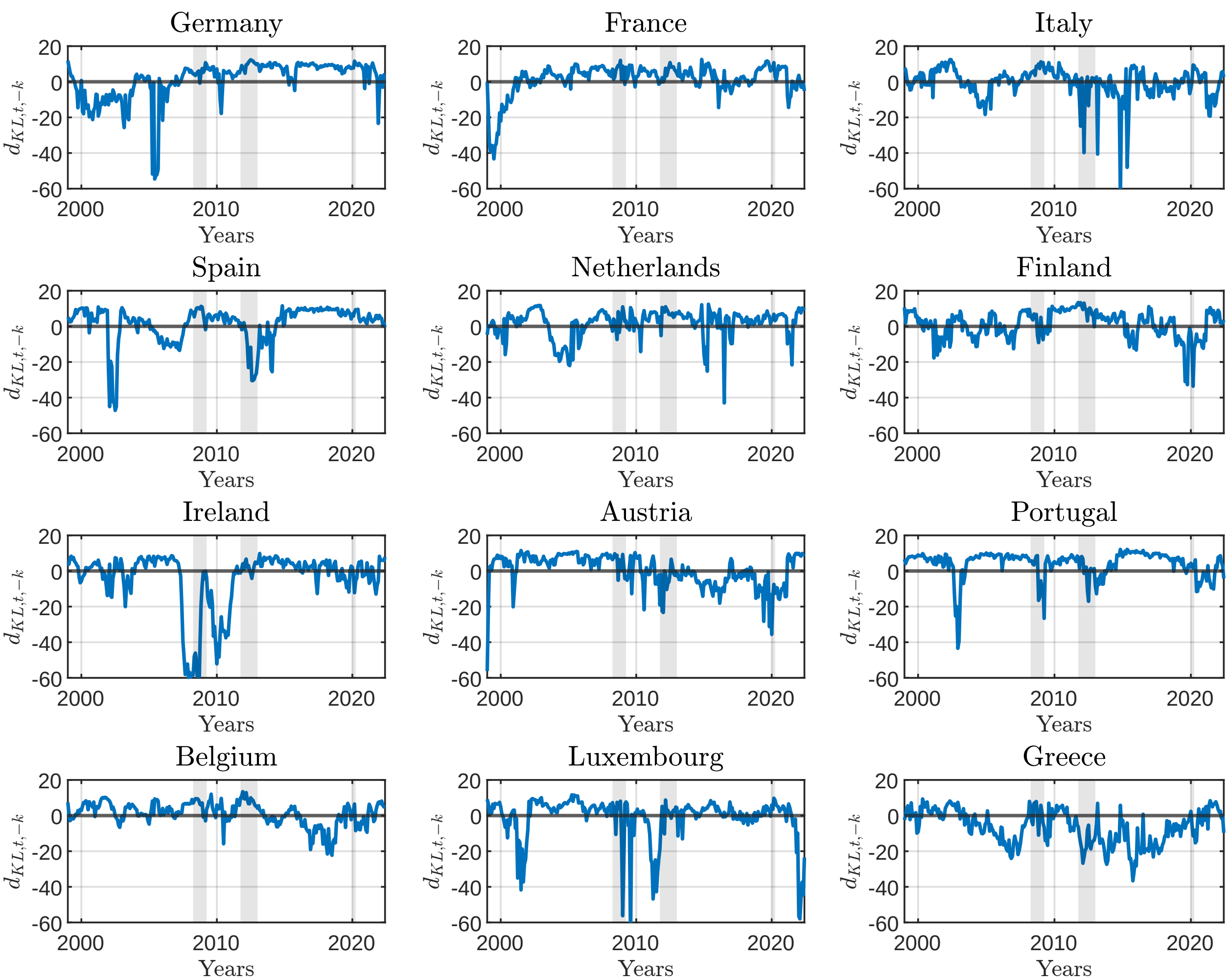
Figure D1. The Risk of Inflation Dispersion by Forecast Horizon



Note: The figure shows the evolution of KL divergence $D_{KL,t}(h)$ at horizons $h = 3$, 12, 18, and 24 defined by equation (3), over the sample period. Gray shaded areas indicate CEPR-dated recessions.

Appendix E. Country contributions to the dispersion of inflation risks: Results for all countries

Figure E1. Country Contributions to the Dispersion of Inflation Risks



Note: The figure shows the values of $d_{KL,t,-k}$, defined by equation (10) for each country k over the sample period. Gray shaded areas indicate CEPR-dated recessions.