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INFLATION AT RISK: THE CASE OF GERMANY

LUCREZIA IMPECIATI

Work project carried out under the supervision of:

Paulo M. M. Rodrigues

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Abstract

This study applies quantile regression to the examination of inflation at risk in Germany. By looking at coefficient estimates, the paper shows how risk factors have diverse impacts at different inflation percentiles. The investigation further extends to the comparison of short-term and long-term forecasting models, emphasizing how sensitivity changes shape inflation trends. Furthermore, for significant years, future core inflation distributions are constructed, allowing for the visual representation of the evolution of inflation at risk.

Keywords: Inflation, Quantile regression, Probability distribution, macroeconomic linkages

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Introduction

In the realm of economic analyses, the examination of the relationship between inflation fluctuations and economic and financial variables has been a longstanding and deeply explored area. Traditionally, scrutinises of inflation dynamics have always been focused on mean-centric approaches, allowing for valuable results into average trends. However, in recent times, with the occurrence of financial crises and an increase in uncertainty, conventional methods fall short of capturing shifts in the macroeconomic scenario, compelling the need for a more nuanced inspection of the inflation phenomenon. This paper embarks on the exploration of inflation in Germany, employing a procedure that goes beyond mean-targeted regressions. Indeed, quantile regression is used, allowing us to delve into the entire spectrum of inflation percentiles to capture non-linearities and state dependencies that might emerge in the context of economic upheaval. The analysis starts by showcasing coefficient estimates from both OLS, used as a benchmark, and quantile regressions. These regressions shed light on interesting patterns and impacts exhibited by macroeconomic variables across various quantiles on the dependent variable. The study continues extending the focus to forecasting horizons, comparing the one-quarter ahead (1Q-ahead) and four-quarter ahead (4Q-ahead) models. This comparative analysis served to emphasize sectoral variability and changes in sensitivity, revealing the implications of responses and the potential effectiveness of steady policy measures in shaping long-term inflation trajectories in Germany, highlighting short-term impacts first. Finally, the future core inflations' distributions are constructed and calculated over three periods: the year 2000, representing the aftermath of the euro adoption; 2010, representing the euro crisis; and 2020, dominated by the global COVID-19 pandemic. In this regard, the plots of the distributions provide a visual representation of their behaviour employing kurtosis, skewness, and variance, offering insights into the evolution of inflation risk during these deafening years. The paper is structured as follows: the first section delves into a discussion of previously published articles,

highlighting differences and similarities in approaches. Subsequently, the methodology and data section elucidate how the work has been conducted and which data have been employed. Finally, a section on results follows, with all findings strengthened through the illustration of tables and figures referred to in the text and presented in Appendix II to V.

Literature Review

Adrian et al. (2019) extensively delve into modelling the complete future real GDP growth distribution. Their focus lies in analysing the entire distribution rather than solely assessing the average or median forecast. The paper highlights several key points. Regarding the distribution dynamics, it demonstrates shifts in the GDP distribution over time, being symmetric during growth periods and left-skewed amid recessions. The authors also emphasize the imbalance in risks. They highlight how downside risk to the variable of interest shows substantially more variation than upside risk, as evidenced by quantiles, where lower quantiles exhibit notable fluctuations while the upper ones remain more stable in response to current financial conditions. This illustrates a non-linear relationship wherein periods of low volatility precede negative growth outcomes, contributing to what is commonly referred to as the “volatility paradox”. To assess and contrast the risks stemming from diverse points within the distribution, the authors have employed the use of downside and upside entropy, expected shortfall, and expected long rise. This study has contributed to the understanding of the connections between financial stability and macroeconomic performance and suggests the need for models able to account for the nonlinear relationship between them. Different to earlier papers that focused on overall volatility in the period preceding the 2008 financial crisis, this study aimed to emphasise that the decrease in GDP volatility was primarily due to downside risk. This drew attention to financial conditions as crucial determinants of the conditional GDP distribution.

Lopez-Salido and Loria (2021) emphasize how from the 1970s in the USA and the Euro area inflation trends were differently affected given both economic and financial threats. Inflation dynamics research and studies have changed since the outbreak of the stock market crash, leading to thoughts about the possible development of downside risks to the inflation perspective. Accordingly, to analyse inflation courses, the interdependences of the conventional

Phillips curve are no longer exhaustive. Indeed, the authors make use of an augmented Phillips curve model which expands the common regression analysis to diverse inflation quantiles, giving leave to a more distinct inflation risk estimation. Including the distribution's tails analysis when looking at inflation outcomes is pivotal to better discern inflation performances. This allows us to focus beyond average or median inflation figures (Lopez-Salido and Loria, 2021). The study encompasses the use of a regime-switching version of their augmented model which confirms that narrow financial statuses can generate considerable downside risks to the inflation prospect; with companies inclined to excessively cut prices, affecting inflation fluctuations.

Banerjee et al. (2020) examine inflation risks in both advanced and emerging market economies, highlighting how considering the range of potential scenarios in addition to the plausible inflation movement is paramount to visualizing risk estimation effects on monetary policy. Within the paper, the quantile regression techniques widen monitoring factors such as current inflation, exchange rate, the change in oil price in domestic currency and financial conditions. There is a non-linear relationship between the degree of inflation and the distribution of expected inflation (Banerjee et al., 2020). Therefore, the downturn in high inflation suggests that high inflation rates are linked to increased upside inflation exposure. Policy constraints control inflation risks (Banerjee et al., 2020). In this regard, in emerging market economies, embracing inflation-targeting structures reduces the likelihood of higher inflation risks. However, in advanced economies, downside risks to inflation have grown since the Great Financial Crisis as well as being connected to encounter the zero lower bound. Moreover, Banerjee et al. (2020) observed compelling non-linearities with output. On the one hand, during periods of economic weaknesses, the chance of encountering downside risks grows, while on the other, the impact of economic activity on upside risks emerges to be less

relevant. Furthermore, in emerging market economies, exchange rate fluctuations exert a prominent influence on inflation risks, with depreciations increasing the probability of higher inflation risks. Tightening financial conditions boost both up and down inflation risks (Banerjee et al., 2020).

Queyranne et al. (2022) address several questions concerning inflation at risk with evidence from the Middle East and Central Asia areas. The authors opted for a multi-step approach including the estimation of mean inflation outcomes based on various economic variables such as core inflation, output gap and exchange rate, as well as inflation expectations and commodity prices calling attention to the role they play in terms of price setting and shaping future inflation trajectories. Queyranne et al. (2022) to better acknowledge the factors driving high inflation risks, estimated a distribution of possible future core inflation outcomes rather than engaging entirely on point forecasts, with the help of a quantile regression approach. Moreover, the study fits a parametric distribution to inflation quantiles at diverse points, perceiving a shift in the distributions considered primarily given by recent increases in commodity prices. This has led to more volatility and skewed risks toward higher inflation risks. Although analysing how inflation risks have evolved, the research gives insight on how central banks can improve the regulation of such matters, especially, when dealing with upside risks. As a result, Queyranne et al. (2022), propose the use of a Value-at-Risk (VaR) approach to enhance risk communication and mitigation.

Finally, Growth-at-Risk (GaR) and consequently, Inflation-at-Risk (IaR), are useful frameworks to policymakers for evaluating the overall risks a country's economy faces. Growth-at-Risk examines the entire distribution of feasible upcoming economic developments, inclusive of both up- and downside risks (Prasad et al., 2019). It gives guidance on the key

drivers impacting future GDP while considering contrasting growth scenarios and the forecasting horizon. Prasad et al. (2019) argue that systemic risks on economic growth can be assessed with the help of GaR, contributing so, to the implementation of macroprudential policies. Notably, policymakers will appraise the trade-off by adopting such policies and effectively undermine short-term slowdowns and medium-term growth risks by mitigating vulnerabilities of a macroeconomic and financial kind. In this regard, the GaR is now part of the International Monetary Fund's (IMF) macroeconomic surveillance toolkit and is used in both multilateral and bilateral ways when assessing tail risks (Prasad et al., 2019).

Methodology and Data

To acknowledge how inflation behaves, in most cases, investigating what influences the conditional mean of inflation can be sufficient. However, with the appearance of economic and financial crises, a broader outlook is imperative. This involves investigating the predictive inflation distribution's tails responses, for non-linearity and state dependence to be accommodated (Lopez-Salido and Loria, 2021). Accordingly, in this analysis, the conventional mean-targeted regression framework will be extended to consider the entire range of inflation quantiles. In line with existing studies, financial and economic conditions can be employed to foresee the likelihood of distinct inflation outcomes at diverse time frames using quantile projections. Therefore, the capacity to flexibly seize a non-linear relationship arises from the fact that a shock to a macroeconomic variable will exert varying effects on future inflation, contingent upon the position within the distribution (Komunjer, 2013). Technically, a quantile regression framework (Koenker, 2005) will be adopted to generate forecasts of future inflation quantiles, conditional on lagged indicators of financial and economic conditions. Quantile forecasts provide relevant information for generating estimates of the predictive density of inflation. Later, these density forecasts are used to establish a measure for estimating the level of inflation risk related to specific macroeconomic circumstances. In the review of their literature, Prasad et al. (2019) define inflation at risk analysis as a three-step investigation. Hence, the empirical approach includes the selection of macroeconomic risk factors, the relationship set up amidst future inflation and economic variables through quantile regressions and finally, the construction of an inflation distribution employing an estimated set of inflation quantiles to model a parametric allocation (Adrian et al., 2016).

The analysis begins with the consideration of various risk factors. The first risk factor considered is inflation expectation. This variable serves as a forward-looking metric to

encompass insight into the anticipated price movement of companies and individuals, contributing to the assessment of its impact on actual inflation rates. The second risk factor is the nominal effective exchange rate, whose fluctuations notably affect export and import prices, thereby influencing overall price levels. The third risk factor is oil prices. It holds significant importance across multiple industries, with its oscillations impacting production costs and potentially influencing core inflation. Similarly, the inclusion of commodity prices provides a broad view of inflationary pressures. The last risk factor encompassed is the output gap, which highlights both underperformance and overheating in an economy, capturing cyclical influences on core inflation.

In this paper, the variable of interest in the quantile regression analysis is core inflation. Core inflation is determined as the annualized quarterly compound core inflation rate in the interim of period t and period $t+h$, with h representing the specified forecast horizon. The analysis evaluates the following specifications for two distinct horizons, 1 and 4 quarters ahead, respectively:

$$\pi_{t+h}^* = \alpha^q + \beta_n^q neer_t + \beta_{oil}^q oil_t + \beta_{\pi}^q \pi_t^{LTE} + \beta_Y^q Y_t + \beta_{CP}^q CP_t + \varepsilon_{t+h}^q \quad [1]$$

where π_{t+h}^* denotes future inflation h quarters ahead for quantile q , with $q \in \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9\}$. The β^q s are coefficients linked to each explanatory variable included in the regression and α^q and ε_{t+h}^q denote the constant and error terms, respectively. As mentioned earlier, quantile regressions are quantified at different points of the distribution of π_{t+h}^* . As a result, each β^q coefficient specifies the macroeconomic relationship between the risk factors and upcoming inflation at different locations across the whole distribution of the same.

Furthermore, quantile regression estimates conditional quantiles of the dependent variable π_{t+h}^* conditional on economic variables $X_{i,t}$. In this regard, for a given period t , in the analysis, we evaluate a linear model for the conditional inflation quantile, whose projected value is:

$$\hat{Q}[\pi_{t+h}^{*q} | X_t] = \hat{\alpha}^q + \hat{\beta}_n^q X_{n,t} + \hat{\beta}_{oil}^q X_{oil,t} + \hat{\beta}_\pi^q X_{\pi,t} + \hat{\beta}_Y^q X_{Y,t} + \hat{\beta}_{CP}^q X_{CP,t} \quad [2]$$

Moreover, setting a regression of this kind calls for a direct forecast based on a timeframe-tailored predictive model, where the dependent variable is a projected value over multiple periods (Marcellino et al., 2006). It is also considered more efficient in matters of parameter estimates as well as exhibiting greater robustness compared to the iterated one (Cox, 1961; Klein, 1968). Indeed, employing quantile regression to evaluate the conditional estimates offers several advantages including the delivery of the optimum unbiased linear estimator of the conditional quantiles and robustness to outliers (Koenker, 2005).

Given the estimated conditional quantiles, the conditional inverse cumulative distribution function (CDF) of future core inflation, which is a skewed t-distribution, can be depicted (Azzalini and Capitanio, 2003).

$$Q_q[\pi_{t+h}^{*q} | X_t] = F_{\pi_{t+h}^*}^{-1}(q | X_t) \quad [3]$$

Accordingly, the probability distribution function is obtained using the parametric t-skew fit (Adrian et al., 2019). The distribution is characterized by four parameters: μ_t (the mean), σ_t (standard deviation), λ_t (degrees of freedom), and η_t (skewness). To derive these coefficients, the approach involves minimizing the square distance between the estimated quantile function and the quantile function of the skewed t-distribution (Equation 4), where

$tsk.quantile(q, \mu_t, \sigma_t, \lambda_t, \eta_t)$ represents the quantile q of the t-skew distribution with parameters (mean, standard deviation, degree of freedom, and skew).

$$[loc, scale, skew] = argmin \left[\sum_q \{tsk.quantile(q, \mu_t, \sigma_t, \lambda_t, \eta_t) - \hat{Q}[\pi_{t+h}^{*q} | X_t]\}^2 \right] \quad [4]$$

The future core inflation distributions will be projected for three periods over the sample considered for both the 1-quarter and 4-quarters ahead models.

The dataset employed in this study is collected quarterly, capturing the German economy fluctuations and trends. The sample spans from 1997:Q1 to 2023:Q3. Further details about the data sources are shown in Appendix I.

Results

For the following analysis, Table 1 represents the coefficient estimates for both the OLS regression, used as a benchmark, and the quantile regression. Figure 1 shows the coefficient plot for the estimates corresponding to 10th, 25th, 50th, 75th and 90th percentile and for OLS (red line). Overall, the trend associated with the Nominal Effective Exchange Rate (NEER) is positive, suggesting that a depreciation in the euro currency confers a growth to inflation. A boost that can result, possibly, from an increase in import costs. However, the stability of this relationship shows dissimilarity among percentiles and variation in sensitivity. The most significant impact appears at the sixth quantile according to which a one-unit increase in NEER corresponds to an increase of 0.053 units in core inflation. Differently, the strength of this correlation weakens at the 80th percentile, suggesting that the impact is less influential in the interim of economically unprosperous periods. Yet, at the 90th percentile, the relationship is negative. This brings warn at extreme values where a downward pressure may be employed on inflation. For what concerns Oil Prices, the relationship with core inflation starts to diminish at the median, suggesting an initial less stressful impact on the dependent variable when oil prices slightly rise. Moreover, an interesting finding appears at the subsequent quantile where a negative coefficient is shown (-0.001), highlighting how high oil prices can have dampening outcomes on inflation. Interpretations for this result can be multiple. For example, global economic conditions can be considered. The regular positive relationship between oil prices and inflation can be altered by a decrease in demand, a consequence of a previous economic recession. Furthermore, the demand-side factor goes alongside. During periods of economic uncertainty, which the dataset includes, cuts on spending from enterprises depending on oil may occur as well as how the structure of energy markets and cooperation with other commodities have evolved. Therefore, market dynamics and unexpected events such as geopolitical tensions and pandemics could impact the influence that adjustments to oil prices have on inflation at

diverse points in the inflation distribution. Inflation expectation, in contrast to what was perceived until now, both with the OLS and quantile coefficients, depict a negative link with core inflation. The most significant negative outcomes are identified at the highest extreme values, 80th and 90th percentile, respectively. Accordingly, acutely high inflation expectations are related to considerable decreases in core inflation. This outline displays how the vulnerability of core inflation in Germany to the independent variable in question differs across inflation frameworks. Some of the quantile regression coefficients associated with the Output Gap are not statistically significant. This gives us the idea of how the level of economic activity on the one hand, does not regularly impact core inflation and on the other, how it may not persistently disturb inflation at diverse points in the distribution; not being so, responsible for short-term inflation fluctuations. Still, a substantial effect on the dependent variable can be observed around the median until a negative shift at the ninth quantile. This suggests that high degrees of economic participation are influenced by overproduction or demand congestion. Finally, for Commodity Prices we can observe a negative relationship throughout all the quantiles considered. At the extreme of the distribution (90th percentile), the significant coefficient signals a meaningful negative effect corresponding to a decline in core inflation in Germany. The correlation, as previously stated, is consistent, yet with diverse magnitudes. The tails of the distribution reflect potential macroeconomic risks and disruptions such as an increase in both demand and supply constraints and global economic tendency, which in turn, can carry dangerous exposures to price stability.

For the four-quarter ahead (4Q-ahead) model results, a comparative analysis with the one-quarter ahead (1Q-ahead) model will follow. Table 2 illustrates a conspicuous increase in the OLS coefficient for the NEER in contrast to the aforementioned model. This evidence implies a prolonged impact of the independent variable on core inflation when the forecasting horizon

is enlarged. However, a nuanced pattern is observed in the quantile coefficients, which, on average, exhibit smaller magnitudes. These findings suggest a reduction in sectoral variability, highlighting that the influence of exchange rates is more sustained over the long term. This is in contrast with the 1Q-ahead model, where an immediate effect and sector-specific responses were the direct implication of short-term impact. In this regard, there will be space for steady policy measures which will contribute to foreseeable inflation trajectories in Germany, shaping the Euro area economic outlook. The OLS estimate for Oil Price in the 4Q-ahead Core Inflation model signifies a robust and highly statistically significant relationship. It shows that a one-unit change in the risk factor is related to a 0.016 increase in core inflation. This robustness underscores the noteworthy impact of oil prices over the long term, possibly influenced by shifts in energy costs and production inputs. Notably, the 4Q-ahead model presents more sustained results compared to the 1Q-ahead model, especially at the extreme tail and around the median. At the 20th and 70th percentile, the coefficient estimates suggest the persistence of the protracted effect that oil prices have on inflation even in less volatile economic conditions. This can be the outcome of continuous cost pressure on businesses and households, which in turn, contribute to the constant impact over an extended time horizon. At the extreme value (90th percentile), instead, the increased sensitivity of oil prices can be captured, suggesting a high responsiveness during challenging economic scenarios. Furthermore, at the first quantile the effect of Inflation Expectation is consistent with the OLS result, illustrating that a decrease in the independent variable will result in a decline in core inflation; suggesting awareness from consumers when inflation expectation lowers in the long term. At the median, the impact is smaller compared to the 1Q-ahead model (Figure 2). The same occurs at the 90th percentile. However, the value is substantial and negative, implying a notable decrease in core inflation that could lead to a reduction in spending and investment. On average, the influence of the Output Gap on core inflation is reduced in the 4Q-ahead model compared to the 1Q-ahead.

Different to what was observed in the previous model, where a negative impact was exhibited, a positive relationship is showcased across all quantiles. This contrast is particularly evident at the highest percentiles, highlighting more significant effects during flourishing economic scenarios. In this context, a positive output gap contributes significantly to higher inflation. In the realm of Commodity Prices, the 4Q-ahead model reveals narrower magnitudes of influence compared to the 1Q-ahead model, notably at the lowest and highest extremes of the distribution, as well as at the median. Such discrepancy may stem from the extended forecasting horizon or from more constrained economic conditions, wherein the nuanced impact of commodity prices unfolds over the long term. Nevertheless, both models consistently exhibit a negative relationship with the dependent variable, signalling a propensity for downward inflation when commodity prices decline. This alignment underscores the resilience of the correlation among diverse fiscal schemes, deepening the likelihood of demand dynamics and deviations in production costs on inflation reactions.

The core inflation distributions are examined across three timeframes within the sample period, for both the 1Q and 4Q-ahead models, to evaluate the potential for deviations from expected inflation, both positive and negative. Specifically, the analysis focuses on three major crises Germany faced between 1997 and 2023. The analysis includes distributions for the year 2000, assessing implications one year after the adoption of the euro, the year 2010 representing the euro crisis, and finally, the year 2020, capturing the Covid-19 pandemic crisis.

As highlighted in Figure 5, the kurtosis of the distribution suggests a greater cluster of values around the mean concerning a normal one, implying a growth in the probability of significant inflation deviations. Additionally, the variance supports this observation, as values are dispersed across the mean. Moreover, the distribution is skewed to the right, a characteristic

that underscores the presence of a moderated majority of values above the mean rather than below it. For macroeconomic concerns, performance at the tails and inflation risks, the nature of such distribution can be explained by several factors. Most notably, the uncertainty surrounding the adoption of a new currency played a significant role. In this context, investors were more inclined towards foreseeing higher inflation, particularly given the strong economic growth Germany was experiencing at the time. Overall, the 2010 core inflation distribution exhibits a fat-tailed and left-skewed pattern compared to the 2000 distribution. This suggests a more unpredictable and volatile inflation scenario (Figure 6), characterized by an increased probability of extremely low inflation outcomes. The negative skewness could be attributed to the deflationary pressures arising from the Euro crisis. Conversely, the more proactive response to inflationary pressure by central banks in the year 2000 likely contributed to the reduced kurtosis for that year, reflecting higher inflation expectations. In the 2020 distribution (Figure 7) the pronounced kurtosis and slightly positive skewness are likely linked to the significant supply chain disruptions and increment in government spending triggered by the COVID-19 pandemic. These factors implied a higher risk of inflation swings, both positive and negative, throughout the period analyzed. Moreover, the German economy was experiencing a recession during this time, leading to downward pressure on inflation in the short term. However, this can conceivably lead to a build-up in inflationary burden in the medium to long-term stage.

Figure 6 illustrates a comparison between the 1Q-ahead and 4Q-ahead core inflation distributions for the year 2000. The distributions exhibit changes in terms of variance, skewness, and kurtosis, implying a shift in the dynamics of inflation over the long term given a distribution largely spread out and characterized by longer tails. Moreover, the mean appears to be greater for the 4Q-ahead model, suggesting an upward trend in inflation expectation in the future. To counteract potential destabilizations, central banks might increase interest rates, for inflation to be back at its targeted levels. However, this change can possibly slow down

economic growth given borrowing and investment to be resulting more expensive. Furthermore, having an increase in kurtosis sheds light on higher chances of extreme events such as sharp spikes in inflation that could potentially lead to a deflationary collapse. Contrary to the previous analysis, the distributions for both 1Q and 4Q ahead for the year 2010 show some similarities (Figure 7). However, a difference can be depicted in the 4Q-ahead distribution's variance which appears to be greater. This suggests an impending increase in uncertainty regarding the actual value of core inflation over this specific period. While both distributions display positive skewness, the 4Q-ahead one is higher. Accordingly, this implies a heightened probability of higher inflation extremes in the long term compared to the short one. Kurtosis seems more peaked and with heavier tails indicating an increased likelihood of having both high and extremely low inflation events at the 4Q-ahead horizon. In this scenario, the economic environment is conducive to higher and more volatile inflation and the associated risks brought about by uncertainty will, again, lead to increased investment caution and a subsequent reduction in economic growth. In the context of the 2020 distributions, both time horizons exhibit a positive mean, implying an overall expectation of increasing inflation in the future. However, a distinction arises for the 4Q-ahead horizon, according to which a discernibly higher mean suggests a potential upward trend. This might raise concerns about the erosion of purchasing power over time. Instead, in terms of variance and kurtosis (Figure 8), a wider range of possible inflation outcomes and a higher chance of extreme events, both high and low, may occur. These dynamics pose challenges for investment decisions and financial management, as the boost in uncertainty may conduce to resource allocation threats. Furthermore, the skewness in the 4Q-ahead distribution indicates a more pronounced asymmetry, allowing for more significant deviations from the mean towards higher inflation. In this context, there might be room for inflation spikes to occur in the future. Indeed, the 4Q time span could dampen economic growth given the potential for a reduction in consumer spending.

Conclusion

Valuable insights for the dynamics and likely drivers of inflation in Germany were possibly to be highlighted utilizing core inflation distributions and forecasting horizons over the diverse timeframes considered. In this regard, the analysis of coefficient estimates from OLS and quantile regression models acknowledged how the relationship and the sensitivity over the dependent variable changed across different percentiles with respect to all the key macroeconomic factors considered. Notably, the correlation between NEER and inflation revealed that in a context where import costs increase, a depreciation in the country's currency might affect inflation growth. The results for oil prices suggested, instead, how global demand oscillations and changes in the energy market play a pivotal role in shaping the direction as well as strengthening the correlation with core inflation given both positive and negative values that have been depicted. Interesting is the finding with inflation expectation. For both time horizons, the link with the variable of interest results in being negative. Accordingly, high inflation expectations are associated with a decrease in core inflation, particularly at the tails. Commodity Prices and Output Gap propose conversely experiences. On the one hand, when commodity prices decline, inflation is inclined to follow a downward trend, while on the other, given the positive relationship that the output gap showcased, higher inflation is associated to an increment in economic participation. Indeed, comparing the two models underscores the relevance of considering forecasting horizons implying the need for steady policy measures to shape long-term inflation dynamics. Furthermore, the examination of core inflation distributions over periods of great uncertainty and economic disruptions, emphasized how risks are heightened in the short run leading to possible long-term impacts. The 2010 distribution, reflecting the Euro crisis indicated increased volatility and deflationary pressure. The 2020 pandemic crisis, evidenced the changes in economic sectors and macroprudential policies, as

evidenced by the kurtosis and skewness results, while the 2000 crisis highlighted risks and concerns following the appreciation of a new currency and its related dynamics.

Within the analysis conducted so far, there are identifiable gaps and opportunities for further research. The current study focuses primarily on macroeconomic factors such as oil prices and currency exchange rates, potentially overlooking crucial microeconomic elements such as companies' behaviours and price-setting mechanisms. Incorporating these aspects could contribute to providing a more complete picture of the economic landscape. Moreover, the methodological choices, encompassing models like OLS and quantile regression, are acknowledged. Nevertheless, diversifying the approach by integrating models like the Vector Autoregressive (VAR) might offer a more effective representation of inter-variable dynamics, fortifying the research reliability. Furthermore, the recognition of different forecasting timeframes is a positive step. However, more concise research on how short-term fluctuations contribute to long-term trends may reinforce it. Finally, the analysis's resilience and predictive accuracy can be achieved by incorporating techniques such as regime-switching models or Bayesian inference to better deal with uncertainty and unforeseen occurrences, yielding more accurate predictions; and improving the overall quality of the analysis.

Appendix I – Data Sources

| Variable | Source |
|--|--|
| Core Inflation - EuroStat Germany Core HICP | Bloomberg Economics |
| Output Gap - Germany Output Gap Estimate | Bloomberg Economics |
| Nominal Effective Exchange Rate - Germany NEER Broad | Bloomberg Economics |
| Inflation Expectation - ZEW Germany Inflation Exoectations | Bloomberg Economics |
| Oil Price - Generic 1st 'CL' Future | Bloomberg Economics |
| Commodity Prices - IMF World Community Price Index | IMF International Financial Statistics |

Appendix II – OLS and Quantile Regression Results and Coefficient Plots for One-Quarter Ahead Core Inflation

| | Dependent Variable: | | | | | | | | | |
|---------------------------------|----------------------------------|--------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|---------------------|----------------------|
| | One-Quarter-Ahead Core Inflation | | | | | | | | | |
| | OLS (1) | tau = 0.1 (2) | tau = 0.2 (3) | tau = 0.3 (4) | tau = 0.4 (5) | tau = 0.5 (6) | tau = 0.6 (7) | tau = 0.7 (8) | tau = 0.8 (9) | tau = 0.9 (10) |
| Nominal Effective Exchange Rate | 0.037 (0.029) | 0.039 (0.028) | 0.011 (0.028) | 0.004 (0.031) | 0.011 (0.033) | 0.013 (0.032) | 0.053 (0.033) | 0.038 (0.034) | 0.001 (0.051) | -0.004 (0.064) |
| Oil Price | 0.014*** (0.005) | 0.005 (0.005) | 0.008 (0.005) | 0.008 (0.005) | 0.007 (0.006) | 0.005 (0.005) | -0.001 (0.005) | 0.002 (0.006) | 0.019 (0.012) | 0.035** (0.014) |
| Inflation Expectation | -0.011*** (0.002) | -0.005* (0.003) | -0.004 (0.003) | -0.003 (0.003) | -0.003 (0.003) | -0.002 (0.003) | -0.003 (0.004) | -0.006 (0.004) | -0.013** (0.005) | -0.015*** (0.004) |
| Output Gap | 0.092 (0.059) | 0.073* (0.041) | 0.083* (0.045) | 0.088* (0.051) | 0.085 (0.056) | 0.103* (0.054) | 0.111* (0.056) | 0.090 (0.065) | 0.046 (0.110) | -0.038 (0.204) |
| Commodity Prices | -0.009*** (0.003) | -0.003 (0.003) | -0.005 (0.003) | -0.005 (0.003) | -0.006 (0.004) | -0.004 (0.004) | -0.001 (0.004) | -0.002 (0.004) | -0.003 (0.005) | -0.012** (0.006) |
| Observations | 106 | 106 | 106 | 106 | 106 | 106 | 106 | 106 | 106 | 106 |

Note: *p<0.1; **p<0.05; ***p<0.01

Table 1: Regression Table for One-Quarter Ahead Core Inflation (standard errors in brackets)

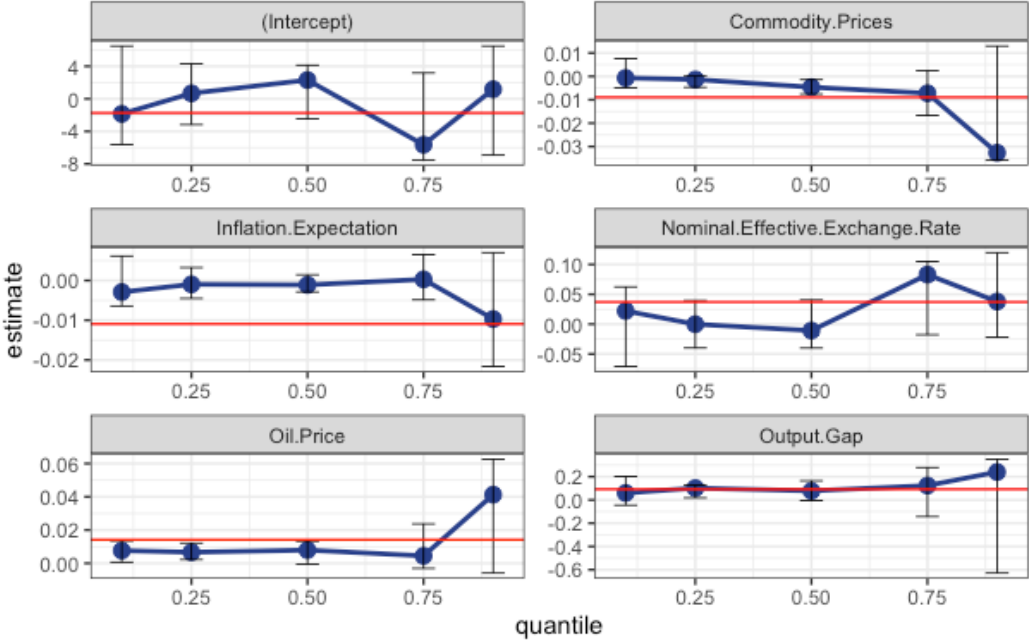


Figure 1: Coefficient Plot for One-Quarter Ahead Core Inflation (the red line represents the OLS regression)

Appendix III - OLS and Quantile Regression Results and Coefficient Plots for Four-Quarter Ahead Core Inflation

| | Dependent Variable: | | | | | | | | | |
|---------------------------------|-----------------------------------|--------------------|---------------------|---------------------|--------------------|--------------------|---------------------|--------------------|-------------------|----------------------|
| | Four-Quarter Ahead Core Inflation | | | | | | | | | |
| | OLS (1) | tau = 0.1 (2) | tau = 0.2 (3) | tau = 0.3 (4) | tau = 0.4 (5) | tau = 0.5 (6) | tau = 0.6 (7) | tau = 0.7 (8) | tau = 0.8 (9) | tau = 0.9 (10) |
| Nominal Effective Exchange Rate | 0.043 (0.032) | 0.022 (0.035) | 0.001 (0.024) | -0.007 (0.023) | -0.001 (0.021) | -0.011 (0.024) | 0.011 (0.033) | 0.028 (0.040) | 0.065 (0.044) | 0.038 (0.056) |
| Oil Price | 0.016*** (0.006) | 0.008** (0.004) | 0.007*** (0.002) | 0.007** (0.003) | 0.007** (0.003) | 0.008* (0.004) | 0.008 (0.005) | 0.006 (0.006) | 0.010 (0.014) | 0.041** (0.019) |
| Inflation Expectation | -0.003 (0.003) | -0.003 (0.003) | -0.001 (0.002) | -0.0001 (0.002) | -0.0001 (0.002) | -0.001 (0.002) | -0.001 (0.002) | -0.0004 (0.004) | 0.0001 (0.006) | -0.010 (0.008) |
| Output Gap | 0.084 (0.065) | 0.060 (0.058) | 0.098*** (0.030) | 0.106*** (0.034) | 0.076** (0.032) | 0.078** (0.039) | 0.068 (0.056) | 0.066 (0.082) | 0.157 (0.119) | 0.240 (0.158) |
| Commodity Prices | -0.011*** (0.004) | -0.001 (0.003) | -0.002 (0.002) | -0.002 (0.002) | -0.003 (0.002) | -0.005* (0.002) | -0.008** (0.004) | -0.007 (0.005) | -0.012 (0.009) | -0.033*** (0.008) |
| Observations | 103 | 103 | 103 | 103 | 103 | 103 | 103 | 103 | 103 | 103 |

Note: *p<0.1; **p<0.05; ***p<0.01

Table 2: Regression Table for Four-Quarter Ahead Core Inflation (standard error in brackets)

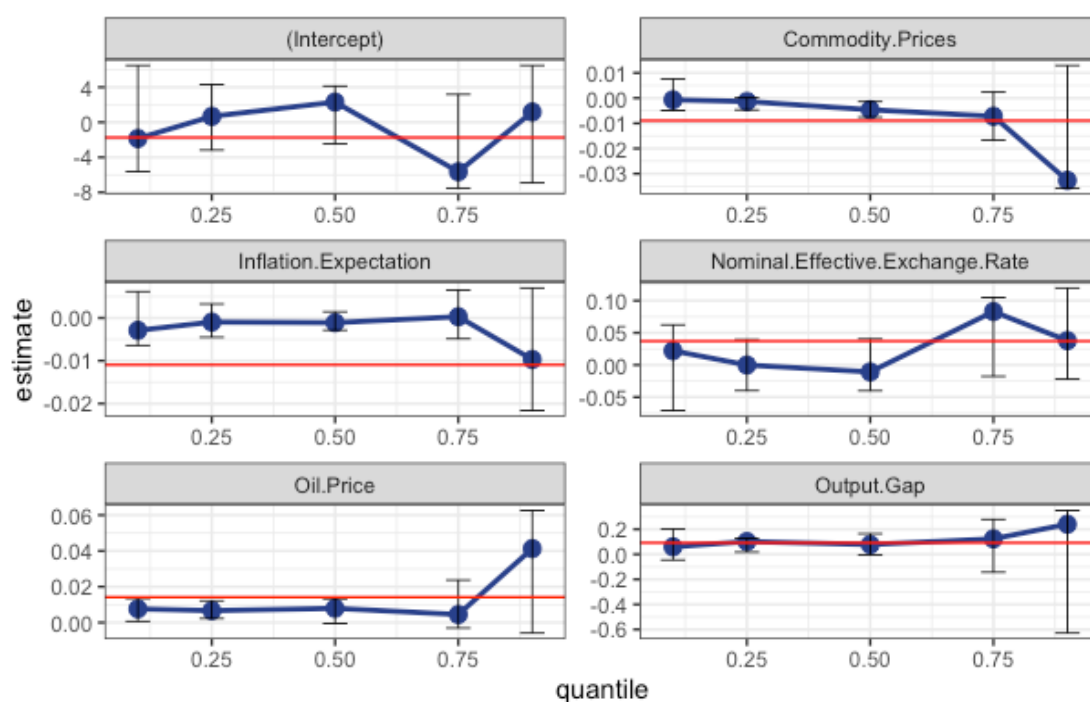


Figure 2: Coefficient Plot for Four-Quarter Ahead Core Inflation (the red line represents the OLS regression)

Appendix IV – One-Quarter Ahead Core Inflation Distributions

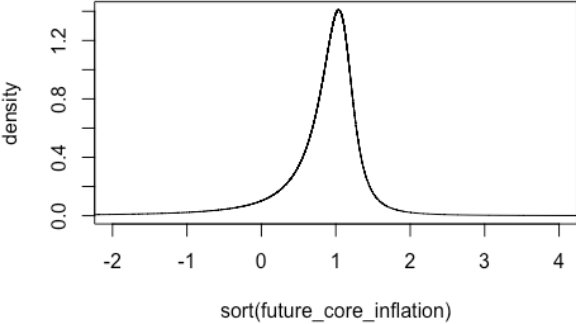


Figure 3: Year 2000 (one year after the adoption of the Euro)

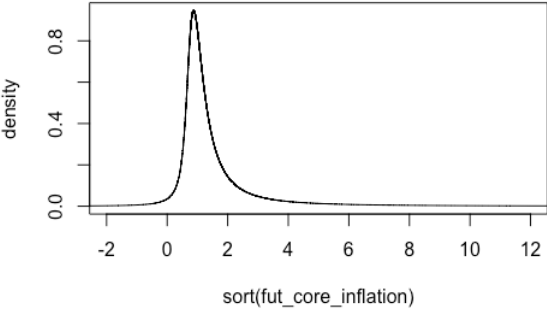


Figure 4: Year 2010 (Euro Crisis)

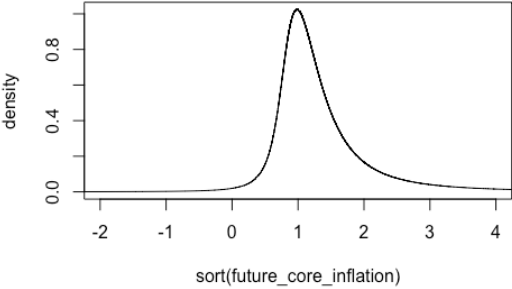


Figure 5: Year 2020 (Covid-19 pandemic crisis)

Appendix V – Four-Quarter Ahead Core Inflation Distributions

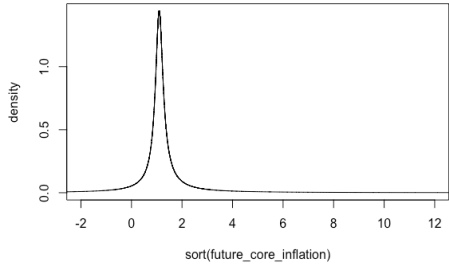


Figure 6: Year 2000 (one year after the adoption of the Euro)

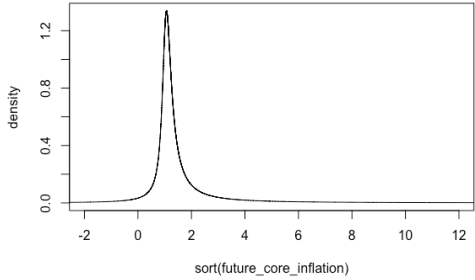


Figure 7: Year 2010 (Euro Crisis)

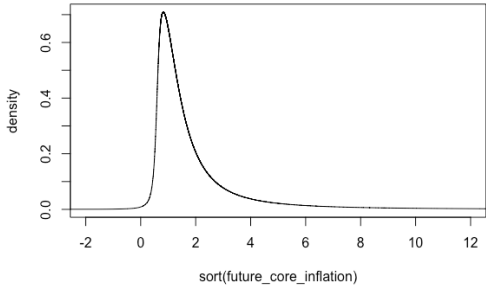


Figure 8: Year 2020 (Covid-19 pandemic crisis)

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