The Distributional Impact of Money Growth and Inflation Disaggregates: A Quantile Sensitivity Analysis *

Matteo Iacopini† Aubrey Poon‡ Luca Rossini§ Dan Zhu¶

August 11, 2023

Abstract

We propose an alternative method to construct a quantile dependence system for inflation and money growth. By considering all quantiles, we assess how perturbations in one variable's quantile lead to changes in the distribution of the other variable. We demonstrate the construction of this relationship through a system of linear quantile regressions. The proposed framework is exploited to examine the distributional effects of money growth on the distributions of inflation and its disaggregate measures in the United States and the Euro area. Our empirical analysis uncovers significant impacts of the upper quantile of the money growth distribution on the distribution of inflation and its disaggregate measures. Conversely, we find that the lower and median quantiles of the money growth distribution have a negligible influence on the distribution of inflation and its disaggregate measures.

Keywords: Inflation; Money Growth; Quantile Regression; Quantile Sensitivity.

*Luca Rossini acknowledges financial support from the Italian Ministry of University and Research (MUR) under the Department of Excellence 2023-2027 grant agreement "Centre of Excellence in Economics and Data Science" (CEEDS).

†Queen Mary University of London, United Kingdom. m.iacopini@qmul.ac.uk

‡Örebro University, Sweden. aubrey.poon@oru.se

§University of Milan, Italy. luca.rossini@unimi.it

¶Monash University, Australia. dan.zhu@monash.edu

1 Introduction

Dependence between random variables refers to the relationship or association between two or more. It describes how the values of one random variable can affect or influence the values of another random variable. Understanding the dependence between random variables is crucial in various areas of probability theory, statistics, and data analysis. Using linear regression, the standard approach for estimating dependence between two random variables involves fitting a linear model to the data and examining the relationship between the predictor and response variables. Despite its popularity, this framework inherently models only the conditional mean of the response variable. Still, it fails to uncover the intricate dependencies that may exist within various regions of the joint distribution. Consequently, it is a somewhat limited approach to describe the dependence between the two variables. When dependence beyond the conditional mean is of interest, a more general approach relies on quantile regression (Koenker and Bassett, 1978), which allows to investigate the effects of a variable on the entirety of the distribution of the response.

The relationship between inflation and money growth has garnered considerable attention in the field of empirical macroeconomics (see Lucas, 1980; Sargent and Surico, 2008; Benati, 2009). This relationship was particularly crucial during the inflationary period of the 1970s and 1980s. However, adopting inflation targeting in most advanced economies during the 1990s weakened this relationship due to sustained periods of low and stable inflation. The recent resurgence of inflation and the expansion of the money stock during the COVID-19 pandemic has revitalized interest in this relationship among policymakers and researchers (see Laidler, 2021; King, 2022; Borio et al., 2023). Consequently, this study examines the distributional impact of money growth on inflation and its disaggregate measures in the US and the Euro Area.

We also investigate whether there is evidence of temporal variation in the distributional impact of money growth on inflation. To the best of our knowledge, our study is the first to explore the relationship between inflation and money growth in a distributional context. Previous studies have solely examined this relationship through the perspective of the conditional mean of the distribution and have led to conflicting findings (see Grauwe and Polan, 2005; Gertler and Hofmann, 2018). The main advantage of our study is that we can directly investigate the effects of excessive money growth (or the upper quantile of the money growth distribution) on the distribution of inflation.

In recent years, there have been significant advancements in economics exploring the application of alternative dependence measures. A notable proposal in this regard is the Conditional Value-at-Risk (CoVaR, see Tobias and Brunnermeier, 2016), which utilizes a system of quantile regressions (Koenker and Bassett, 1978) to assess the escalation of tail co-movement among financial institutions. For example, these measures provide the change in the financial system's 1% quantile when a specific institution experiences its 1% quantile. However, the linear construction proposed in the paper results in the unfortunate limitation that the percentage point change in response to the 1% and 99% quantiles is the same.

To overcome this limitation, we propose an alternative approach to constructing a quantile dependence system for inflation and money growth. Our approach assumes that with a sufficiently long time series of lagged past observations, denoted as $\mathbf{z}_t$, we can reliably estimate the system of conditional quantiles for both inflation and money growth, which become functional representations of $\mathbf{z}_t$. Therefore, by employing linear projections, we can determine the sensitivity of inflation quantiles to changes in the quantiles of money growth. This allows us to capture the intricate relationship between inflation and money growth across different quantiles.

In contrast to the CoVaR approach, it is important to note that the responsiveness of inflation to the 10% money growth quantile might differ from its responsiveness to the 90% money growth quantile. The proposed alternative approach recognizes and accounts for the potential variation in the impact of different quantiles of money growth on inflation. This allows for a more nuanced understanding of how inflation responds to varying levels of money growth throughout the distribution.

Our empirical analysis reveals a significant positive influence of the upper quantile of the money growth distribution on the distribution of inflation and its disaggregate measures in the United States and the Euro area. Specifically, we find evidence of an increasing positive skewness in the overall distribution of US Personal Consumption Expenditure (PCE) inflation and Euro area Harmonised Index of Consumer Prices (HCPI) inflation. This upward skewness primarily stems from a shift in the distribution of services inflation towards higher values. In contrast, we find no significant impact of the lower quantile of money growth on the distribution of inflation and its disaggregate measures in both US and Euro area.

Moreover, our analysis uncovers that, at the median quantile, money growth has a relatively negligible distributional effect on inflation. Only in the extreme tails of the money growth distribution do we observe a substantial impact on the overall distribution of inflation. Thus, our results suggest that the relationship between inflation and money growth is weak during periods of economic tranquillity, as indicated by the median quantile of the money growth distribution. It is only during exceptional events, such as the COVID-19 pandemic, that this relationship becomes significant.

Furthermore, we find evidence of temporal variation in the distributional impact of money growth on inflation and its disaggregate measures between the US and the Euro area. Specifically, our results show a higher positive skewness in the overall distribution of US PCE inflation and services inflation following the COVID-19 pandemic. However, in the Euro area, we only find evidence of increased positive skewness in the overall distribution of HCPI inflation and services inflation during 2015. This effect is likely attributed to the implementation of quantitative easing (QE) measures by the European Central Bank (ECB) at the beginning of 2015.

This article is organized as follows. Section 2 introduces and describes the quantile dependence framework. Section 3 details the empirical application undertaken in the paper. Section 4 presents the results derived from our empirical analysis. Finally, Section 5 concludes.

2 Methodology

2.1 A system of quantiles

Consider a time series of n-dimensional random vectors, $Y_t \in \mathcal{Y} \subset \mathbb{R}^n$, and its natural filtration $\mathcal{F}_t = \sigma(\{Y_t, Y_{t-1}, \ldots\})$, defined on the index set $\mathbb{Z}$. Then, there is a k-dimensional random vector $Z_t \in \mathcal{Z} \subset \mathbb{R}^d$ such that

$$\mathbb{P}(Y_{t+h} \in A|\mathcal{F}_t) = \mathbb{P}(Y_{t+h} \in A|Z_t), \qquad \forall A \in \mathcal{F}_{t+h} \tag{1}$$

for all $t \in \mathbb{Z}$ and $h \in \mathbb{Z}_+$. Furthermore, we assume the time series is strictly stationary, which implies that the h steps ahead forecasting distribution for the ith variable in the system can be defined as:

$$Y_{t+h,i}|Z_t = \mathbf{z}_t \sim P_{h,i}(Y_{t+h,i}|\mathbf{z}_t), \tag{2}$$

for any $i = 1, \ldots, n$. Therefore, conditioning on $Z_t = \mathbf{z}_t$, the associated τth quantile, with $\tau \in (0, 1)$, is given by:

$$Q^\tau_{i,h}(\mathbf{z}_t) = \inf\left\{\mathbf{y} \in \mathcal{Y}_i,\ P_{h,i}(\mathbf{y}|\mathbf{z}_t) \leq \tau\right\}, \tag{3}$$

where $\mathcal{Y}_i$ denotes the support of the ith variable in the system.

In the following, we consider the quantile linear regression (QR) model as

$$Y_{t+h,i} = Q^U_{i,h}(\mathbf{z}_t) = \mathbf{z}'_t\boldsymbol{\beta}^U_i, \qquad U \sim \mathcal{U}(0, 1), \tag{4}$$

where U and Z_t are independent and $\boldsymbol{\beta} \in \mathbb{R}^k$ is a vector of coefficients. Our approach focuses on the standard quantile regression as of Koenker and Bassett (1978) assuming exogeneity. When endogeneity is of concern, we suggest using instrumental variables (IV) to alleviate the issue based on the IVQR approach of Chernozhukov and Hansen (2008).

Based on the quantile regression model, Equation (3) implies that

$$Q_{i,h}^{\tau} := Q_{i,h}^{\tau}(\mathbf{z}_t) = \mathbf{z}_t' \boldsymbol{\beta}_{ih}^{\tau}. \tag{5}$$

The coefficient vector can be estimated by solving the minimisation problem:

$$\widehat{\boldsymbol{\beta}}_{ih}^{\tau} = \arg\min_{\boldsymbol{\beta}} \sum_{t=1}^{T} \rho_{\tau}\big(y_{t+h,i} - \mathbf{z}_t' \boldsymbol{\beta}\big), \tag{6}$$

where $\rho_{\tau}(x) = x(\tau - \mathbb{I}(x \leq 0))$ is the check loss function at quantile τ and $\mathbb{I}(\cdot)$ is the indicator function.

2.2 Quantile Sensitivities

Several studies have explored the dependence between different quantiles of various variables. One notable work in this area is the study by Tobias and Brunnermeier (2016), which introduces the concept of Conditional Value at Risk (CoVaR). Given a system of time series, the CoVaR represents the Value at Risk (VaR) of one variable conditional on the event that another variable reaches its VaR. This approach provides insights into the tail dependence and extreme risk associated with the joint behaviour of different variables. In particular, this concept is interesting because it elicits the riskiness of one variable in the future, given that another variable is already at risk. Precisely translated into our notation, the CoVaR of the h steps ahead τth quantile of the ith variable given the one step ahead τ'th quantile of the jth variable defined as:

$$\mathbb{P}\big(Y_{t+h,i} \leq \mathrm{CoVaR}_{h,1}^{\tau,\tau'} | Z_t,\, Y_{t+1,j} = Q_{j,1}^{\tau'}\big) = \tau. \tag{7}$$

Another attempt is made by Lee et al. (2021), who formulate the problem in a VAR structure. Building on the VAR literature, they propose a quantile impulse response function (QIRF) as the change of the τth quantile of the ith variable in response to an exogenous shock to the system, that is:

$$\mathrm{QIRF}_i^{\tau}(h) \coloneqq \frac{\partial Q_{i,h}^{\tau}}{\partial \boldsymbol{\epsilon}_t}, \tag{8}$$

where $\boldsymbol{\epsilon}_t$ is the vector of mean zero disturbances with a diagonal covariance matrix decomposed from the standard mean regression structural VAR. Instead, Chavleishvili and Manganelli (2021) propose a different quantile impulse response function to perform stress tests in a structural quantile VAR (QVAR) model that captures nonlinear relationships among macroeconomic variables. Finally, Han et al. (2022) propose several ways of constructing and estimating quantile impulse response functions through local projection methods.

Our approach differs from theirs by accounting for the potential variation in the impact of different quantiles of money growth on inflation. In particular, we combine the approaches of Tobias and Brunnermeier (2016) and Lee et al. (2021) and define the quantile sensitivity as the responsiveness of the h steps ahead quantile of a variable of interest to the change of the 1 step ahead quantile of another variable.

Definition 2.1 (Quantile Sensitivity)**.** *Given an n-dimensional time series process Y_t, with $n > 1$, the quantile sensitivity ($\mathcal{QS}$) of the h steps ahead quantile of the ith variable with respect to the change of the 1 step ahead quantile of the jth variable, $\mathcal{QS}_{i,j,h,1}^{\tau,\tau'}$, is defined as:*

$$\mathcal{QS}_{i,j}(h;\tau,\tau') \coloneqq \frac{\partial Q_{i,h}^{\tau}}{\partial Q_{j,1}^{\tau'}}. \tag{9}$$

Consider the relationship between $\widetilde{Q}_{i,h}^{\tau}$ and $\widetilde{Q}_{j,1}^{\tau'}$ as represented by:

$$\widetilde{Q}_{i,h}^{\tau} = f\big(\widetilde{Q}_{j,1}^{\tau'}\big). \tag{10}$$

Then, using a first-order Taylor approximation of $f(\cdot)$ about $Q_{j,1}^{\tau'}$ yields:

$$
\begin{aligned}
f\big(\widetilde{Q}_{j,1}^{\tau'}\big) &\approx f\big(Q_{j,1}^{\tau'}\big) + \frac{\partial f}{\partial \widetilde{Q}_{j,1}^{\tau'}}\bigg|_{\widetilde{Q}_{j,1}^{\tau'}=Q_{j,1}^{\tau'}} \times \big(\widetilde{Q}_{j,1}^{\tau'} - Q_{j,1}^{\tau'}\big), \\
\widetilde{Q}_{i,h}^{\tau} &\approx Q_{i,h}^{\tau} + \frac{\partial Q_{i,h}^{\tau}}{\partial Q_{j,1}^{\tau'}} \times \left(\widetilde{Q}_{j,1}^{\tau'} - Q_{j,1}^{\tau'}\right) \\
&\approx Q_{i,h}^{\tau} + \mathcal{QS}_{i,j}(h;\tau,\tau') \times \left(\widetilde{Q}_{j,1}^{\tau'} - Q_{j,1}^{\tau'}\right),
\end{aligned}
\tag{11}
$$

which implies that the change of the τth quantile of variable i, $\widetilde{Q}_{i,h}^{\tau} - Q_{i,h}^{\tau}$, in response to a change the τ'th quantile of variable j, $\widetilde{Q}_{j,1}^{\tau'} - Q_{j,1}^{\tau'}$, are proportional, with a proportionality factor given by the quantile sensitivity $\mathcal{QS}$.

Moreover, by considering all $\tau \in (0,1)$, we can assess the relationship between perturbations in the τ'th quantile of variable j and the resulting changes in the entire h steps ahead distribution of variable i. This allows for a comprehensive analysis of how different quantiles of one variable are associated with variations in the distribution of another variable over multiple steps ahead.

2.3 Estimation of the Quantile Sensitivities

The quantile sensitivity defined in Equation (9) involves expressing $Q_{i,h}^{\tau}$ as a function of $Q_{j,1}^{\tau'}$. In this section, we demonstrate the construction of this relationship using linear quantile regressions. By utilizing linear quantile regression, it is possible to estimate the conditional quantiles of variable i given different quantiles of variable j, thus allowing to quantify the sensitivity of $Q_{i,h}^{\tau}$ to changes in $Q_{j,1}^{\tau'}$.

Without the loss of generality, we consider a set of quantile levels $\boldsymbol{\tau} = \{\tau_1, \ldots, \tau_k\}$, $k > 1$. Let $\mathbf{q}_{j,1} = \big(Q_{j,1}^{\tau_1}, \ldots, Q_{j,1}^{\tau_k}\big)' \in \mathbb{R}^k$ be a k-dimensional vector of quantiles for variable j, with $j \in \{1, \ldots, n\}$. Assuming a homogeneous model across all quantile levels, we have:

$$
\mathbf{q}_{j,1} = \mathbf{B}_{j,1}\mathbf{z}_t, \tag{12}
$$

where $\mathbf{B}_{j,1} \in \mathbb{R}^{k \times d}$ denote the matrix-variate quantile coefficients. We can now construct the system of quantiles of the one step ahead predictive distribution as:

$$\mathbf{Q}_1 = (\mathbf{q}'_{11}, \mathbf{q}'_{21}, \dots, \mathbf{q}'_{n1})' = \mathbf{B}_1 \mathbf{z}_t, \tag{13}$$

with $\mathbf{B}_1 = (\mathbf{B}'_{11}, \mathbf{B}'_{21}, \dots, \mathbf{B}'_{n1})' \in \mathbb{R}^{nk \times d}$. Assuming that $\mathbf{B}'_1 \mathbf{B}_1$ is invertible, we have

$$\mathbf{z}_t = \left(\mathbf{B}'_1 \mathbf{B}_1\right)^{-1} \mathbf{B}'_1 \mathbf{Q}_1. \tag{14}$$

A similar construction can be obtained for the collection of h steps ahead conditional quantiles:

$$\mathbf{Q}_h = \mathbf{B}_h \mathbf{z}_t = \mathbf{B}_h \left(\mathbf{B}'_1 \mathbf{B}_1\right)^{-1} \mathbf{B}'_1 \mathbf{Q}_1. \tag{15}$$

Thus, Equation (9) can be obtained by selecting elements from the $(nk \times nk)$ matrix:

$$\overline{\mathbf{B}}_{h,1} = \mathbf{B}_h \left(\mathbf{B}'_1 \mathbf{B}_1\right)^{-1} \mathbf{B}'_1. \tag{16}$$

In this formulation, it is important to note that the linear projection approach assumes time-homogeneous dependence. This implies that the matrix describing the interlink between quantiles does not depend on z_t and is assumed to be constant over time. Therefore, the linear construction utilised in this article assumes a static relationship between the variables and does not consider potential time-varying dynamics in the dependence structure between the variables.

Nonetheless, the static dependence implied by the linearity assumption still allows us to investigate how the distribution of inflation changes in response to a change in money growth at different time periods. This is because, given the set of quantile regression coefficients, we can find the quantile level of the observed money growth at time t, that is:

$$\tau_t = \inf\{\tau \in (0,1) : \mathbf{z}'_t \boldsymbol{\beta}_{i,\tau} < y_{t,j}\}. \tag{17}$$

Then

$$\mathcal{QS}_{i,j}(h;\tau,\tau_t) = \frac{\partial Q^{\tau}_{i,h}}{\partial Q^{\tau_t}_{j,1}} \tag{18}$$

gives the responsiveness of the quantiles at $t+h$ of any other variable i to a change at time $t+1$ of the money supply from its current level.

3 Data description

In this real-data application, we investigate the response of change in money growth to inflation. Therefore, we set $Y_{i,t+h}$ as the inflation measure and $\mathbf{Z}_t$ as the matrix of covariates, comprising an intercept term along with lagged values of both money growth and inflation. As for the forecast horizons, we focus on the 12 months (or 1-year) ahead forecast, thus setting $h = 12$.

Moreover, to deeper the analysis of the relationship between these key macroeconomic variables, we apply the proposed $\mathcal{QS}$ measure to both US and European data, with the aim of identifying common behaviours and idiosyncratic features.

The US PCE inflation data were collected from the St. Louis Fred database, while the Euro Area HCPI inflation data were obtained from the ECB statistical data warehouse. In our analysis, we adopt M3 as the designated measure of money supply for both economies, and the M3 data for both countries was also acquired from the St. Louis Fred database.

Regarding inflation, the two sources provide also data disaggregated by macro-sectors but use different classifications for the latter. Therefore, we focus on four PCE disaggregated measures for US inflation: Durables, Non-durables, Services, and Energy Goods and Services. Instead, for the Euro Area, we focus on six HCPI disaggregated measures: Unprocessed Food, Processed Food, Industrial Goods excluding energy, Services, and Energy. Notice that applying the proposed method to different components of inflation as well as its overall series allows us to better investigate the reaction of inflation to money growth by disentangling the effects on the different macro-sectors.

Our dataset consists of monthly data from February 1960 to March 2023 for the US and from February 1997 to March 2023 for the Euro Area. All data are transformed into log-differenced month-on-month growth rates to account for unit root non-stationarity.

4 Empirical Results

This Section reports and discusses the main findings for the two economies. First, we examine the effect of money growth on the distribution of inflation and its disaggregated measures. Second, we assess the existence of potential temporal variation in the distributional effects of money growth on inflation. All the empirical analyses have been performed by assessing the impact of both extreme shocks to money growth ($\tau^M = 0.10$ and $\tau^M = 0.90$) and "ordinary" or changes to the median ($\tau^M = 0.50$). For each of them, we investigated its impact on the entire distribution of the inflation variable, as approximated by the fine grid of quantiles $\tau^I \in \{0.01, 0.02, \ldots, 0.99\}$.

4.1 Distributional Impact of Money Growth on Inflation and its Disaggregate Measures

Figure 1 presents the distributional effect of the one-year ahead money growth impact on US PCE inflation and its four major disaggregated measures across selected quantiles. The findings reveal that at the 10th quantile, money growth significantly negatively impacts the entire distribution of durable goods inflation (i.e., for every level of τ^I). However, a change in the lower quantile of money growth does not have a significant distributional impact on the other three disaggregated measures and on the overall PCE inflation. This is mainly driven by the high uncertainty of the (positive but not significant) impact on services inflation. Turning to the upper tail of money growth, specifically the 90th percentile, a significant positive impact is observed on the right tail of the overall PCE inflation. This effect leads to an increase in the thickness of the distribution tail and a rightward skewness. Furthermore, this rightward skewness contributes to the asymmetry of the PCE inflation distribution. In terms of the disaggregated measures, shocks to the upper tail of money growth also result in thicker-tailed but symmetric distributions for both PCE non-durable goods and energy (goods and services) inflation. Instead, for PCE service inflation, we find evidence of a significant rightward shift in the distribution. However, the upper quantile of money growth does not significantly affect PCE durable goods inflation. Summarising, these findings suggest that the increasing positive skewness observed in the overall PCE inflation distribution due to changes in the upper quantile of money growth is mainly driven by the shift in PCE service inflation towards the right.

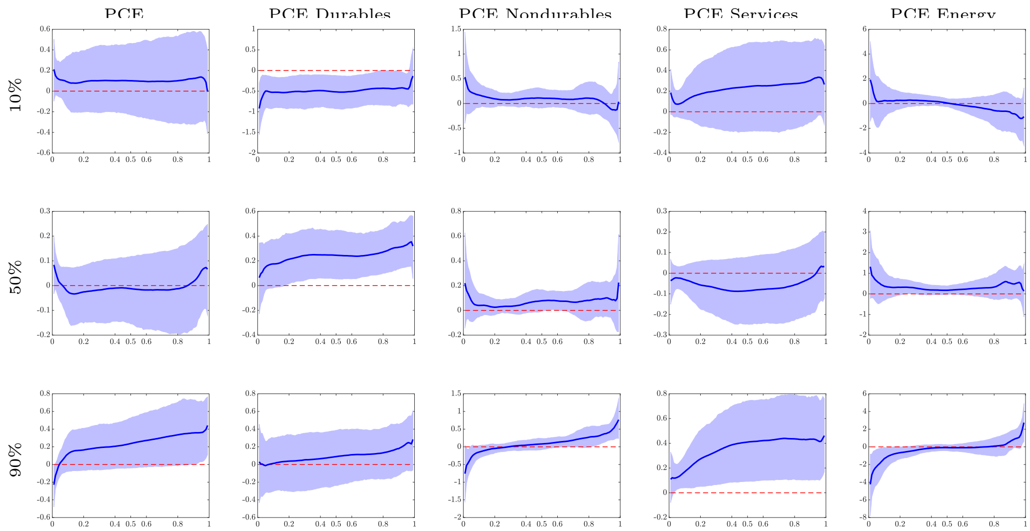

Figure 1: Distributional impact of the 1-year ahead impact of money growth on US PCE inflation across selected quantiles $\tau^M \in \{0.10, 0.50, 0.90\}$. Notes: the thick blue line represents the mean quantile responses of the 1-year ahead impact of money growth on US PCE inflation. The shaded blue area represents the 68% bootstrapped confidence interval.

We also present the distributional effect of the 1-year ahead money growth impact on Euro area HCPI inflation and its five major disaggregated measures across selected quantiles in Figure 2. Similarly to the US case, our findings indicate that at the lower quantile (specifically, the 10th percentile) money growth does not significantly impact HCPI inflation and its associated disaggregated measures. However, for the upper quantile of money growth, we find a discernible shift of the rightmost part of the distribution of overall HCPI inflation, manifesting as right skewness. This emerges from the positive impact on all the quantiles $\tau^I > 0.45$. Moreover, these extreme changes to the right tail of money growth are found to increase in magnitude along the quantiles of the HCPI distribution, thus resulting in a significant right-skewing effect. Overall, this shift contributes to an increase in the thickness of the tails and an asymmetry in the distribution. Notably, the aforementioned distributional shift appears to be primarily driven by HCPI services and energy inflation: the former seems responsible for the level shift (to the right) of the entire HCPI distribution, whereas the latter accounts for the increased right-skewness. On the other hand, the upper quantile of money growth does not exert a significant distributional impact on HCPI inflation is related to unprocessed, processed, and industrial goods.

Consequently, the empirical results for both the US and the Euro area suggest that, at the upper quantile of money growth (or in the presence of excess money growth), the distribution of inflation becomes more positively skewed, with services playing a crucial role in this distributional shift, followed by the energy sector and durable goods. Conversely, at the 10th percentile as well as at the median of money growth, we find no substantial distributional impact on inflation and its disaggregated measures in both the US and the Euro area. This (negative) finding is of crucial importance as it highlights that conditional mean or median approaches are not adequate for modelling the relationship between money growth and inflation. Alternative methods that investigate other parts of the entire distribution of the response, such as quantile regression, seem preferable. [1]

To better understand the distributional impact of the 1-year ahead effect of money growth on US PCE inflation and Euro area HCPI inflation, we present a three-dimensional plot illustrating this relationship across all quantiles. These graphical representations can be observed in Figures 3 and 4 respectively. A key finding derived from these graphs is that, at the median quantile, money growth exhibits a relatively negligible

[1] We also report the distributional impact of the 1-year ahead impact of money growth for the 25% and 75% quantiles in the supplementary material. These results display very similar dynamics to the 10% and 90% quantiles reported in both the US and Euro Area.

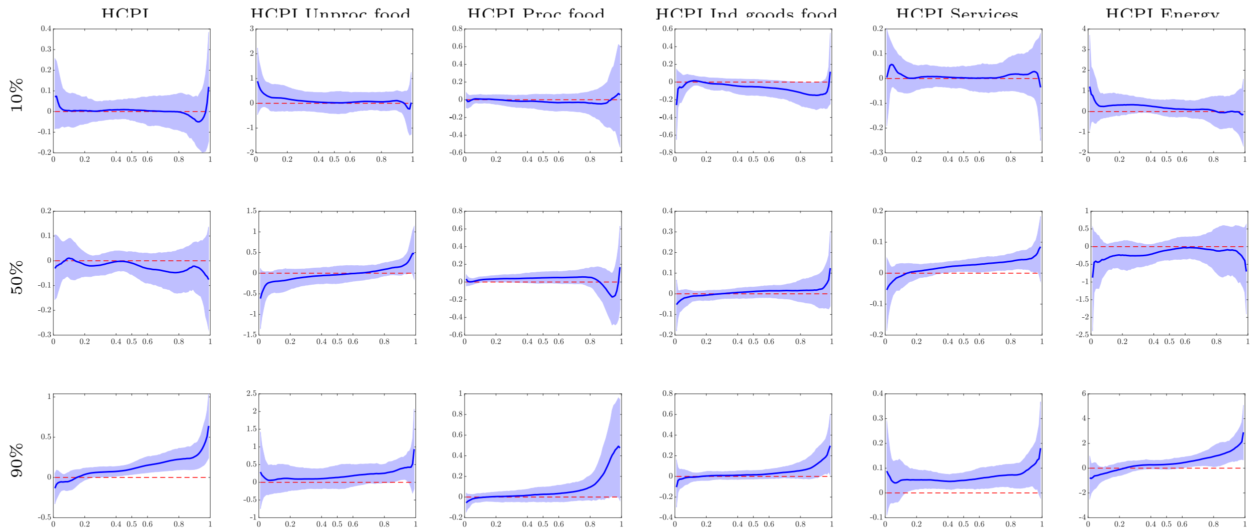

Figure 2: Distributional impact of the 1-year ahead impact of money growth on Euro HCPI inflation across selected quantiles $\tau^M = \{0.10, 0.50, 0.90\}$. Notes: the thick blue line represents the mean quantile responses of the 1-year ahead impact of money growth on Euro HCPI inflation. The shaded blue area represents the 68% bootstrapped confidence interval.

distributional impact on inflation. It is only in the extreme tails of the money growth distribution where a discernible and significant impact on the overall distribution of inflation is observed. Consequently, our results suggest that during periods of economic tranquillity, the relationship between inflation and money (represented by the median quantile of money growth distribution) is highly likely to be tenuous, with a significant relationship observed solely during extraordinary events like the COVID-19 pandemic.

Our findings are aligned with the empirical investigations conducted by Grauwe and Polan (2005) and Borio et al. (2023), which present evidence of a statistically significant positive correlation between excessive money growth and average inflation across select countries. However, the study conducted by Gertler and Hofmann (2018) provides evidence indicating that the connection between money growth and inflation has weakened over time across various countries. In all three of these studies, the relationship between money growth and inflation is examined through the lens of the conditional mean of the distribution, but they yield contradictory results, which is not surprising through the lens of our previously-described findings. Our results, on the other hand, demonstrate that the median quantile of the money growth distribution exerts an insignificant impact on the distribution of inflation. By comprehensively examining the entire distribution of money growth and inflation, we can directly investigate the effects of excessive money growth (or the upper quantile of the money growth distribution) on the distribution of inflation, a perspective that the aforementioned studies cannot provide.

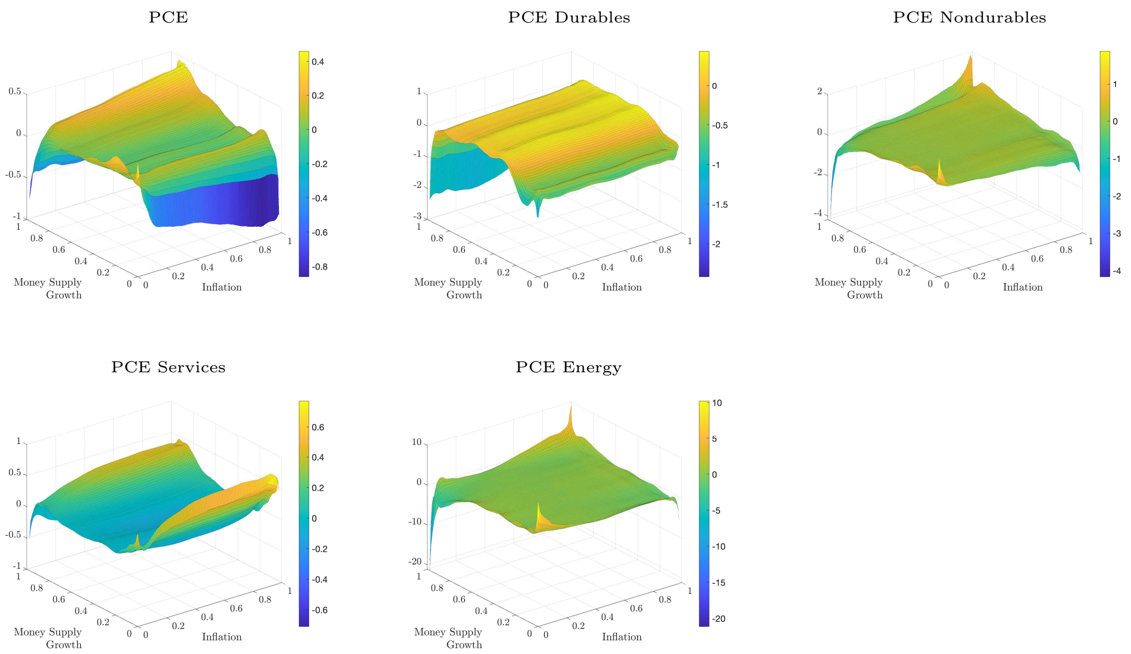

Figure 3: Mean Quantile Sensitivities of the 1-year ahead impact of money growth on US PCE inflation across all quantiles.

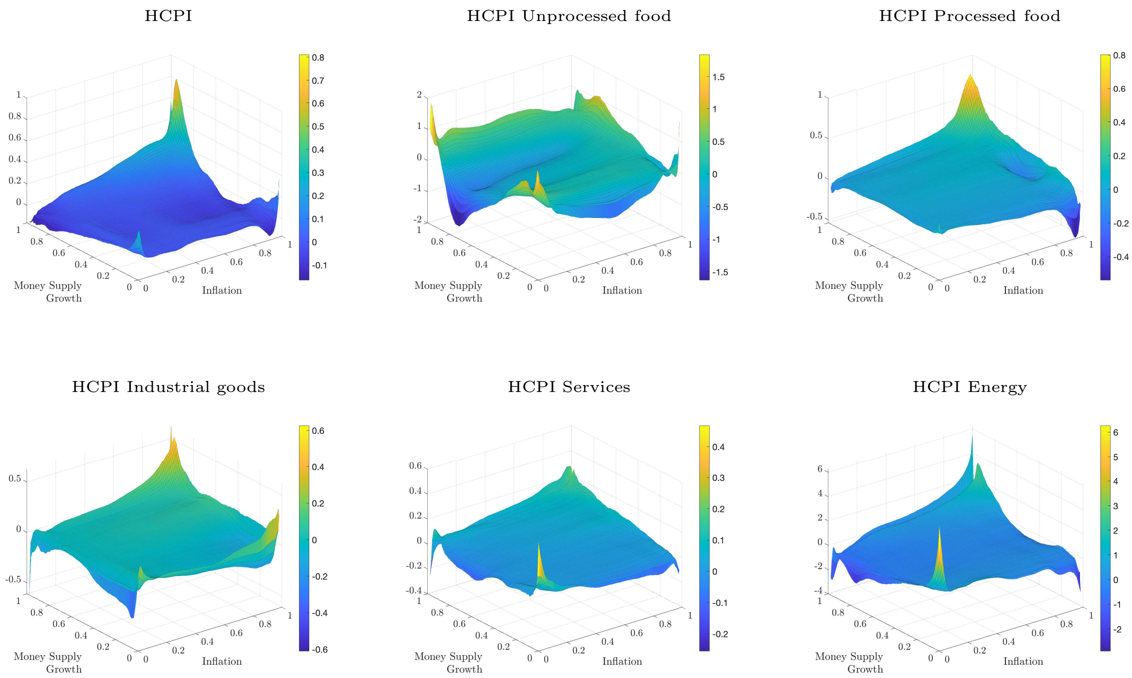

Figure 4: Mean Quantile Sensitivities of the 1-year ahead impact of money growth on Euro HCPI inflation across all quantiles.

4.2 How Does the Distributional Impact of Money Growth on Inflation Change Over Time?

In the previous section, we investigate the quantile sensitivity over the entire sample. However, especially for the US, the time series cover periods characterised by very different features, including great moderation, the financial crisis, and the COVID-19 pandemic. Motivated by the different economic and financial conditions characterising these periods, we aim to investigate whether the quantile sensitivity of inflation to money growth has experienced a variation over time. Specifically, we apply the quantile sensitivity method to investigate how money growth affects the distribution of inflation over certain time periods.

In this exercise, we deviate from the approach of selecting a shock for a specific quantile, as discussed in the previous section (e.g., see Lee et al., 2021). Instead, we calculate the quantile based on the observed money growth itself. It is important to highlight that using the results from the set of quantile regressions, we can obtain the conditional distribution of money growth for the entire observation period. Therefore, substituting the observed value yields the conditional cumulative density function, which is a uniform random variable given the set of regressors. In particular, we define

$$\tau_t = \inf\{u \in (0,1) : \mathbf{z}_t' \boldsymbol{\beta}_u \geq Y_{t+h}^i\}.$$

This approach allows us to illustrate the effect of a perturbation in the money growth rate for a specific period.

Figure 5 illustrates the distributional effect of money growth on US PCE inflation and its disaggregated components during four distinct periods: 1980, 2005, 2009, and 2023.

Overall, the influence of money growth on US PCE inflation appears to be inconsequential throughout the selected time periods. However, evidence suggests that money growth's impact on PCE durable goods and services inflation has changed since the COVID-19 pandemic. Prior to the pandemic, money growth exhibited a negative level-shift distributional impact on PCE durable goods. Subsequently, this impact became insignificant. Conversely, for PCE services inflation, money growth displayed an insignificant distributional effect before the COVID-19 pandemic, which became positive level-shifting and right skewing after the pandemic. In terms of the other two disaggregated measures of inflation, the distributional impact of money growth remains insignificant across the four selected time periods, with the exception of the tails of PCE energy inflation distribution.

The analogous analysis of the distributional impact of money growth on Euro area inflation is reported in Figure 6. In this case, our analysis has focused on the time periods of 2005, 2009, 2015, and 2023, since Euro area inflation data is available only from the late 1990s. Our findings reveal that, in general, the impact of money growth on Euro area HCPI inflation and its disaggregates are statistically insignificant across most of the time periods, except for 2015. Specifically, in 2015, money growth demonstrated a significant effect on the upper tail of the Euro area HCPI inflation distribution, which is characterized by an increase in the right skewness of the distribution.

This observed impact is largely attributed to the positive level shift of the HCPI services inflation distribution, while the increase of skewness is related to the effects on the right tail of the HCPI energy inflation. It is possible that this significant impact of money growth on Euro area inflation is the result of quantitative easing (QE) measures implemented by the European Central Bank (ECB) at the beginning of 2015. However, the significance of this impact appears to have diminished following the outbreak of the COVID-19 pandemic.

In summary, our analyses on both the Euro area and US reveal that the distributional impact of money growth inflation and its disaggregate measures exhibit variation over time.

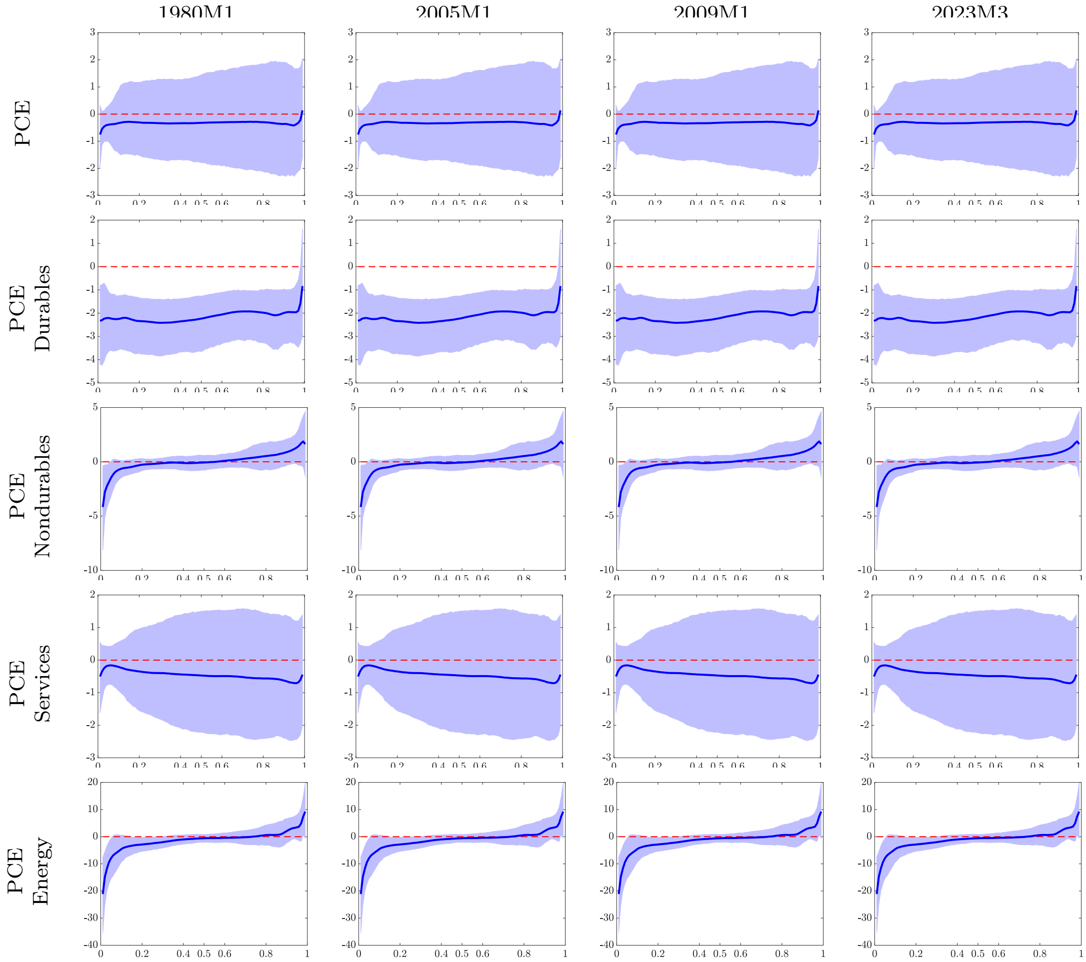

Figure 5: Distributional impact of the 1-year ahead money growth on US PCE inflation for selected time periods: January 1980, January 2005, January 2009, and March 2023. Notes: the thick blue line represents the mean quantile responses of the 1-year ahead impact of money growth on US PCE inflation. The shaded blue area represents the 68% bootstrapped confidence interval.

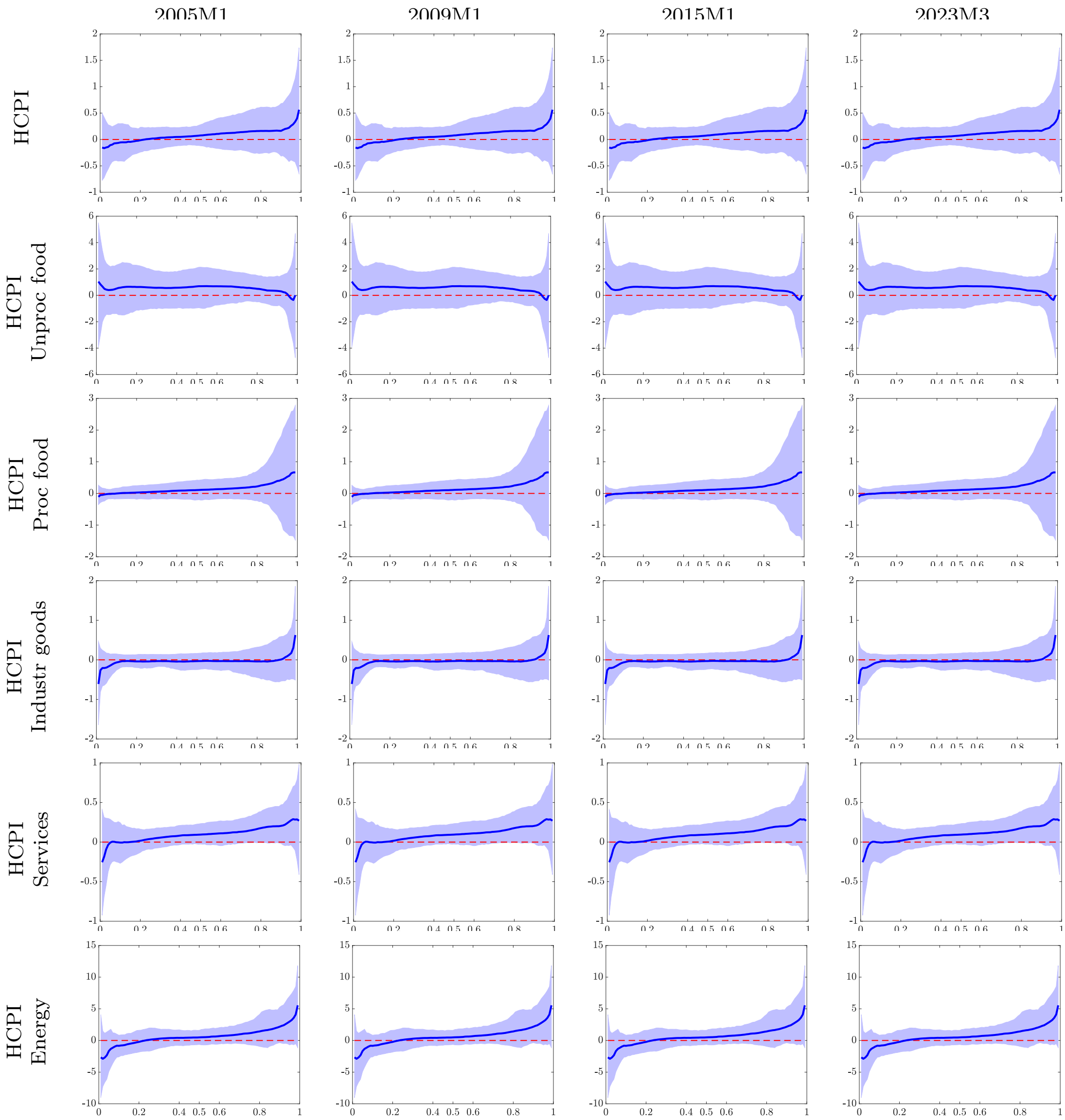

Figure 6: Distributional impact of the 1-year ahead money growth on Euro area HCPI inflation for selected time periods: January 2005, January 2009, January 2015, and March 2023. Notes: the thick blue line represents the mean quantile responses of the 1-year ahead impact of money growth on Euro area inflation. The shaded blue area represents the 68% bootstrapped confidence interval.

5 Conclusion

We proposed an innovative framework for examining the impact of money growth on inflation and its disaggregate measures in the US and the Euro area. Our framework focuses on quantile dependence, providing a novel approach to analyze the distributional effects. This aspect of the relationship between money growth and inflation has not been previously explored in the existing literature.

Through empirical analysis of both economies, we found evidence that variations in the upper quantile of the money growth distribution significantly influence the distribution of inflation and its disaggregate measures, affecting both its level and skewness. On the other hand, the lower and median quantiles of the money growth distribution exhibit a relatively negligible effect on the distribution of inflation.

Our proposed framework is versatile and can be applied to investigate various other macroeconomic or financial phenomena. For instance, it can be extended to explore the relationship between oil prices and stock returns or a growth-at-risk scenario.

References

Benati, L. (2009). Long run evidence on money growth and inflation. Technical report, ECB working paper.

Borio, C., B. Hofmann, and E. Zakrajšek (2023). Does money growth help explain the recent inflation surge? Technical report, Bank for International Settlements.

Chavleishvili, S. and S. Manganelli (2021). Forecasting and Stress Testing with Quantile Vector Autoregression. Technical Report 2330, ECB Working Paper.

Chernozhukov, V. and C. Hansen (2008). Instrumental variable quantile regression: A robust inference approach. *Journal of Econometrics 142*(1), 379–398.

Gertler, P. and B. Hofmann (2018). Monetary facts revisited. *Journal of International Money and Finance 86*, 154–170.

Grauwe, P. D. and M. Polan (2005). Is inflation always and everywhere a monetary phenomenon? *Scandinavian Journal of Economics 107*(2), 239–259.

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

King, M. (2022). Monetary policy in a world of radical uncertainty. *Economic Affairs 42*(1), 2–12.

Koenker, R. and G. Bassett (1978). Regression quantiles. *Econometrica*, 33–50.

Laidler, D. (2021). A personal view from the wrong side of the subsequent fifty years. Technical report, University of Western Ontario, Department of Economics.

Lee, D. J., T.-H. Kim, and P. Mizen (2021). Impulse response analysis in conditional quantile models with an application to monetary policy. *Journal of Economic Dynamics and Control 127*, 104102.

Lucas, R. E. (1980). Two illustrations of the quantity theory of money. *The American Economic Review 70*(5), 1005–1014.

Sargent, T. J. and P. Surico (2008). Monetary policies and low-frequency manifestations of the quantity theory. Technical report, External MPC Unit Discussion Paper.

Tobias, A. and M. K. Brunnermeier (2016). CoVaR. *The American Economic Review 106*(7), 1705.