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THE INFLUENCE OF UNCONVENTIONAL MONETARY POLICY TOOLS: AN EURO AREA PERSPECTIVE

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Abstract. *Purpose* – This article aims to investigate the influence of unconventional monetary policy tools (UMPTs) employed by the European Central Bank (ECB) on the inflation rate and GDP growth rate within the euro area, motivated by the principles of the Taylor rule.

Research methodology – Elastic net regression with ARIMA residuals was used to analyse the relationship between UMPTs and economic indicators, measured by adjusted R-squared. Six samples were constructed, and hypothesis testing was performed using moving block bootstrapping. Residual diagnostics were used for model validation.

Findings – The study revealed significant impacts of UMPTs, particularly in combination with interest rates, on inflation rates. However, adjusted R-square values for GDP growth rate were less pronounced, indicating a more complex relationship. Research contributes to understanding the dynamics of monetary policy transmission mechanisms, informing policy institutions, and guiding future research directions.

Research limitations – Limitations include the focus on the euro area and the absence of analysis in other major economies. Future research should address these limitations and incorporate additional variables for a more comprehensive analysis.

Practical implications – The findings provide insight for policymakers regarding the efficacy of UMPTs in influencing inflation rates, aiding in informed decision-making in monetary policy formulation and implementation.

Originality/Value – This study contributes novelty by comprehensively analysing the relationship between UMPTs and economic indicators within the euro area, providing valuable insight into monetary policy institutions, and guiding future research directions.

Keywords: unconventional monetary policy, European Central Bank, inflation rate, GDP growth rate, elastic net regression.

JEL Classification: E52, E58, C32.

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1. Introduction

Price stability, economic growth, and the resolution of financial vulnerabilities are high on the priority list of the European Central Bank (ECB), which performs a crucial function in the monetary policy framework. The ECB was established in 1998 to address these challenges: multiple nations within this monetary union have their unique monetary systems, and a lack of synchronisation can impede policy alignment and result in economic instability.

Various methodological approaches have been used in academic research to assess the influence of Central Bank policies on national economies. Clarida et al. (1999) laid the groundwork for monetary policy analysis, emphasising forward-looking behaviour, refined by Woodford and Walsh (2005). The Taylor rule (Taylor, 1993) guides interest rate setting, historically the primary tool for central banks. However, the Great Recession prompted the introduction of Unconventional Monetary Policy Tools (UMPTs) (Mulligan, 2021; Eberly et al., 2019), broadening policy options when interest rates are constrained (Lomachynska et al., 2020; European Central Bank, 2021).

Nevertheless, critical literature questions the efficacy of UMPT (Febrero et al., 2015; Finnegan & Kapoor, 2023), leaving ambiguity in its impact on inflation and GDP growth rates.

This study fills gaps by analysing UMPTs' connection to inflation and GDP growth rates across the euro area from 2008 to 2023. Employing elastic net regression with ARIMA residuals quantifies relationships. The *aim* is to clarify the influence of UMPTs on economic indicators, *hypothesising* that UMPTs significantly affect inflation and GDP growth rates.

The results indicate varied impacts of UMPT on economic indicators, contributing to the refinement of dynamic stochastic general equilibrium (DSGE) models and facilitating future policy analysis (de Haan et al., 2020; Mouabbi & Sahuc, 2019). By encompassing the entire euro area and employing a comprehensive set of UMPTs directly employed by the ECB, this research provides valuable insight into the dynamics between UMPTs and key economic indicators. Despite the complexities and challenges in quantifying these relationships, the findings contribute to a deeper understanding of the effectiveness of UMPTs in influencing inflation and GDP growth rates, offering crucial insights for policymakers to navigate future economic challenges.

2. Literature review

For a prolonged duration, interest rates have served as the fundamental pillar of monetary policy for central banks, acting as the primary mechanism to modulate economic operations. Scholars have scrutinised experiences from various nations and discerned various pathways of impact. This long-standing reliance underscores the pivotal role of interest rates in shaping the economic landscape (Belongia & Ireland, 2014; Fedorova & Meshkova, 2021). Saiti et al. (2021) found that in the Republic of North Macedonia, despite the absence of a short-term influence of central bank bills' interest rates on total lending and real GDP, there is a notable long-term negative effect, underscoring the critical role of suitable monetary policy approaches in addressing liquidity imbalances, especially in times of crisis. Contrary to prevailing assumptions, Mahmud and Akuoko-Konadu (2023) demonstrate in their study that restrictive monetary policy does not yield stability in inflation within sub-Saharan Africa. They propose that central banks reassess their strategies and consider lowering policy rates as a tool to target inflation. Their research further emphasises the need to explore alternative inflation management strategies.

In the aftermath of the Great Recession, central banks realised that conventional tools, such as adjustments to interest rates, proved inadequate in stimulating economic recovery. This realisation prompted the introduction of UMPTs (Mulligan, 2021; Eberly et al., 2019). UMPTs are used by central banks when traditional policy rates are constrained by the effective lower bound (Lomachynska et al., 2020; Houcine et al., 2020). They can be integrated into the monetary policy framework, adapted to the specific context, and managed to mitigate side effects (Johnson et al., 2020). The literature reveals a critical examination of the ECB's

UMPTs. Febrero et al. (2015) initially suggested these tools might not fully address eurozone challenges. Hartwell (2019) later questioned their impact on credit provision and inflation. Trifonova (2022) raised concerns about the ECB's ability to implement structural reforms, while Finnegan and Kapoor (2023) argued these tools may not adequately address structural issues. Collectively, these studies form a critical strand of research, suggesting the need for a re-evaluation of the unconventional monetary policy tools.

In the realm of literature dedicated to quantifying the relationship between UMPTs employed by the ECB, inflation, and GDP growth rates, two sub-strands emerge. One distinct sub-strand within the literature is typified by its efforts to forecast primary economic indicators using UMPTs. This approach prioritises predictive accuracy over clarification of the underlying relationships between these indicators. Notable contributions to this substrate include the works of de Haan et al. (2020), Mitchell and Pearce (2020), Ambler and Rumler (2019), Bottone and Rosolia (2019). The second sub-strand focuses on constructing DSGE models, wherein the genuine effects of UMPTs may not be fully understood. Some studies within this sub-strand either fail to encompass the entire euro area, utilise derivative tools instead of a comprehensive list of ECB-employed UMPTs, or overlook the actual effects of these tools, as exemplified by Ouerk et al. (2020), Mouabbi and Sahuc (2019), Geissdoerfer et al. (2017), Horvath and Voslarova, (2017), Zabala and Prats (2020).

The existing body of research on the application of UMPTs by the ECB, while extensive, leaves the ultimate impact ambiguous. This ambiguity underscores a notable research gap that requires clarification of the relationship between UMPTs, inflation, and GDP growth rates. This clarity is imperative to gain valuable insight into the extent to which DSGE models should integrate the effects of UMPTs.

This research aims to address the existing gaps in the literature by focussing on the relationship between UMPTs and two key economic indicators: inflation and GDP growth rates. This focus contributes to the improvement of DSGE models. A unique aspect of our approach is the inclusion of the entire euro area in our dataset, which covers all UMPTs directly used by the ECB. This comprehensive approach highlights the scope of our research.

3. Methodology

This chapter delineates the methodological paradigm implemented in the present investigation and provides an overview of the characteristics inherent to the data utilised in the research.

3.1. Sample characteristics

Our research is primarily focused on the analysis of UMPTs employed by the ECB. This study will also include conventional monitoring tools, such as the interest rates set by the ECB. The rationale behind selecting the ECB for our research is its status as one of the leading and most influential central banks.

The sample period for our study spans from 2008 to 2023. The choice of this timeframe is motivated by the ECB's adoption of unconventional monetary policy measures in response to the global financial crisis that began in 2008. Central banks globally, including the ECB, responded to the crisis by implementing a mix of conventional and unconventional policy measures. Moreover, this period encapsulates noteworthy economic events such as the Great Recession, the Sovereign Debt Crisis, the COVID-19 pandemic, and the Russo-Ukrainian War. Our objective was to accumulate as much data as possible, hence the decision to commence our sample in 2008 and extend it until 2023. This approach allowed us to construct the longest possible time series, thereby enhancing the precision of our results. We used monthly data for both inflation and GDP growth rates. The availability of monthly statistical data for inflation facilitated this process. However, the use of GDP growth rate data presented a challenge due to its quarterly nature. To overcome this, we interpolated the GDP growth rate data to convert them into a monthly format. Consequently, our research was conducted using monthly data, representing the highest frequency data available for variables such as inflation rate and GDP growth. This approach ensures the robustness and reliability of our findings.

The data set was partitioned into two subsets: a training set and a test set. The training set comprised 80% of the total data, while the remaining 20% was assigned to the test set. This division facilitates the evaluation of the performance of the model and its ability to generalise to unseen data.

In this study, we adopt a monetary policy framework that is rooted in the model proposed by Clarida et al. (1999) and subsequently refined by Woodford and Walsh (2005). This framework has been the foundation for numerous esteemed researchers, including but not limited to Campbell et al. (2020), Malmendier et al. (2021), Kryvtsov and Petersen (2021), Campbell et al. (2020), Ravn and Sterk (2021), and Galí (2020). A defining characteristic of this framework is the Taylor rule defined by Taylor (1993). The Taylor rule (Formula (1)) posits that the nominal federal funds rate (r) is influenced by the rate of inflation (p) and the percentage deviation of the real GDP from its long-term linear trend (y). This deviation indicates whether the GDP growth rate is above or below its potential. Thus, the Taylor rule establishes a link between central banks' interest rates, inflation, and GDP growth rates. However, with the introduction of UMPTs, the Taylor rule may not be sufficient to shape the models used by central banks. This provides a rationale for why UMPTs, interest rates, inflation, and the GDP growth rate are the variables of interest in our research. This underscores the significance of these variables in our investigation.

$$r = p - 0.5y + 0.5(p - 2) + 2. \quad (1)$$

The inflation and GDP growth rate data for this study were retrieved from the ECB Statistical Data Portal (ECB Data Portal, n.d.). The data about the unconventional monetary policy tools was extracted from the official website of the ECB. This extraction process involved a careful manual reading of press releases, specifically focussing on the announcements related to the introduction and termination of each unconventional monetary policy tool. The summary of ECB tools is presented in Table 1.

Upon successful retrieval of this information, we constructed dummy variables corresponding to each unconventional monetary policy tool. Each dummy variable was assigned a value of 0 when the respective unconventional monetary policy tool was not in use, and a value of 1 when it was in use.

The base category was defined as the scenario where all unconventional monetary tools were assigned a value of zero, indicating that no unconventional monetary tool was in use and only conventional monetary policy tools were employed. Thus, the base category for this dummy variable regression represents a state where only conventional monetary policy tools were utilised.

Table 1. Introduction and description of the ECB's conventional and unconventional monetary policy tools (source: prepared by the authors)

Tool	Description	Introduction
Conventional Tools		
1. Policy interest rate	The main tool used to influence borrowing costs and stimulate or control economic activity.	The Inception of the ECB in June 1998
2. Open-market operations	The purchase or sale of government bonds and other securities to manage liquidity and interest rates.	The Inception of the ECB in June 1998
3. Minimum reserve requirements	The requirement for banks to have a certain amount of funds in reserve affects the lending capacity.	The Inception of the ECB in June 1998
4. Main Refinancing Operations (MRO)	Provides the bulk of liquidity to banks through auctions, typically conducted weekly.	The Inception of the ECB in June 1998
Unconventional Tools		
1. Long-Term Refinancing Operations (LTROs) (European Central Bank, 2011)	Provision of short-term (3-year) loans to banks to improve liquidity and support lending activity.	December 2011
2. Asset Purchase Programmes (APP) (European Central Bank, 2015)	Buys various types of assets to inject liquidity into the financial system and influence interest rates.	January 2015 (Securities Markets Programme), expanded during the COVID-19 pandemic
3. Targeted Longer-Term Refinancing Operations (TLTROs) (European Central Bank, 2014a)	Offers long-term loans to banks at favourable interest rates to stimulate lending to specific sectors.	September 2014, expanded in response to the COVID-19 pandemic.
4. Pandemic Emergency Purchase Programme (PEPP) (European Central Bank, 2020)	Purchase of various assets to support favourable borrowing conditions during the Covid-19 pandemic.	March 2020
5. Outright Monetary Transactions (OMTs) (European Central Bank, 2012)	Potential purchase of troubled eurozone countries' government bonds in the secondary market.	September 2012
6. Negative Interest Rates (European Central Bank, 2014b)	We are setting policy rates below zero, and charging banks for holding excess reserves to stimulate lending.	June 2014
7. Securities Markets Programme (SMP) (European Central Bank, 2010)	Purchase of government bonds from troubled eurozone countries to stabilise bond markets and reduce costs.	May 2010

As outlined in Table 1, the ECB has employed both conventional tools and UMPTs, such as LTROs, APP, PEPP, OMTs, TLTROs, SMP, and negative interest rates, to address financial challenges and crises since its inception in 1998.

3.2. Model architecture and reasoning for the research methodology

In our research, we employ regression analysis to discern the relationship between the dependent variables (Inflation and GDP growth rate) and the independent variables (Interest rates determined by the ECB and UMPTs), incorporating ARIMA residuals to uphold the assumptions of the regression. The Ordinary Least Squares (OLS) method, renowned for its simplicity, is frequently used for estimating linear models. However, OLS provides optimal estimates of the regression coefficients and their corresponding robust standard errors only when the model adheres to the Gauss-Markov assumptions. In our research, we used the OLS as our foundational model. The insights gleaned from the application of the OLS model form the reference point for our analysis.

$$OLS\,loss = \sum_{i=1}^{n}\left(Y_i - \beta X_i\right)^2. \quad (2)$$

In many instances, including this study, adherence to these assumptions is infrequent. Specifically, in this research, the assumption of multicollinearity might be compromised when multiple interrelated dependent variables are employed. This is evident in the aforementioned loss function (Formula (2)), where Y_i denotes the actual value at time i, β is the parameter derived from OLS, and X_i represents the value of the dependent variable at time i. It can be observed that as the count of dependent variables nears n, the loss function tends towards infinity. When the multicollinearity assumption is breached, the variance of the OLS estimate increases significantly. However, estimators with substantial variances yield suboptimal estimates, a phenomenon known as overfitting.

This study, recognising the potential for multicollinearity when employing multiple interrelated dependent variables, opts for regularisation over the conventional OLS approach to mitigate the risk of overfitting. Regularisation, which includes lasso, ridge, and elastic-net, adjusts or shrinks the estimated coefficient towards zero, discouraging the acquisition of overly complex models. The Elastic-net method (Zou & Hastie, 2005), a generalization of lasso and ridge, is chosen for its ability to balance penalties associated with ridge regression and lasso, thereby reducing reliance on data for variable selection and enhancing model stability. This method, coupled with the inclusion of 3 interest (Deposit facility, main refinancing operations, marginal lending facility) rates as dependent variables and 7 UMPTs (see Table 1) as dummy variables, ensures the complexity of the model is optimal, reducing the likelihood of underfitting and overfitting.

$$ENET\,loss = \sum_{i=1}^{n}\left(Y_i - \beta X_i\right)^2 + \lambda\left(\alpha\sum_{j=1}^{k}\left|\beta_j\right| + \left(1-\alpha\right)\sum_{j=1}^{k}\left|\beta_j\right|^2\right). \quad (3)$$

In Formula (3), α serves as the mixing parameter for the ridge (α = 0) and the lasso (α = 1), while λ is the parameter associated with Lasso. It can be observed that the initial segment of the Elastic-net loss function corresponds to the standard OLS estimation, to which a penalty has been appended.

The Elastic Net regression model's hyperparameters (alpha and lambda) were ascertained through an exhaustive hyperparameter tuning process. The step size for hyperparameter tuning was set at 0.1. The regression parameters were derived through a machine learning process executed in JupyterLab, utilising the Python programming language and the sci-kit-learn library. A comprehensive presentation of the coefficients obtained will be provided in the next Section, titled 'Empirical results and discussion'.

The adjusted R-squared was evaluated through constructed distributions via simulations, employing the Moving Block Bootstrap (MBB) method for time series data. Four distributions were built for the inflation and GDP growth rate samples, with the percentile method used to calculate the confidence intervals. The block size, chosen based on suggestions from Gimenez-Nadal et al. (2019), Calhoun (2018), and Kuffner et al. (2021), was set to exceed the autocorrelation of the time series, as determined by the Autocorrelation Function graph.

Following the application of elastic-net regression, a robustness analysis revealed autocorrelation, heteroskedasticity, and nonnormality within the residuals, prompting the adoption of the ARIMA methodology. This was applied after confirming the stationarity of the residuals via an augmented Dickey-Fuller test and adjusting the integration parameter to zero if necessary. For the AR(p) part of the ARIMA process, Formula (4) was used:

$$X_t = c + \sum_{i=1}^{p} \phi_i X_{t-i} + \epsilon_t . \tag{4}$$

In the given equation, 'p' signifies the count of lagged observations incorporated in the model, symbolising the quantity of autoregressive terms. The parameters denoted by ϕ_i are the coefficients corresponding to the lagged values, which require estimation from the data. The error term, represented by ϵ_t, is the discrepancy between the observed and forecasted values at each temporal point. The constant 'c' can be interpreted as the average value of the time series when the values of $X_{t-\mathrm{i}}$ are nullified.

For the MA(q) part of the ARIMA process, Formula (5) was used:

$$X_t = \mu + w_t + \sum_{i=1}^{q} \theta_i w_{t-i} . \tag{5}$$

In the given equation, 'q' represents the number of lagged observations incorporated in the model, symbolising the number of moving average terms. The parameters denoted by θ_i are the coefficients corresponding to the lagged error terms, which require estimation from the data. The term μ is the mean of the series, and w_{t-i} signifies the error term at time 't' and time $t - i$ respectively.

The hyperparameters (p,q) were derived through a cross-validation hyperparameter tuning process executed in JupyterLab, utilising the Python programming language, the sci-kit-learn library, and the GridSearchCV method. The upper bounds for cross-validation were determined by employing the autocorrelation function (ACF) and the partial autocorrelation function (PACF) or by setting the upper limit at 5, as recommended by Petropoulos et al. (2021).

Upon the execution of the ARIMA procedure on the residuals derived from the elastic net regression, a subsequent robustness analysis was performed. This involved subjecting the residuals of the ARIMA model to tests for autocorrelation, heteroskedasticity, and normality. Through this process, it was discovered that there was an absence of autocorrelation in all instances, and to a significant degree, there was a lack of heteroskedasticity. However, the residuals continued to exhibit non-normality, a crucial factor to consider, particularly when employing the model for forecasting purposes and constructing confidence intervals.

4. Empirical results and discussion

In this chapter, detailed research results are presented, as well as a comparison of the results with previous studies. Moreover, all limitations of the research are highlighted.

Table 2 delineates the hyperparameters of the Elastic Net regression model. The table indicates that the coefficients corresponding to the inflation rate should be subjected to less shrinkage, given the decreasing values of the alpha and lambda parameters. Conversely, the parameters associated with the GDP growth rate require a more substantial degree of shrinkage, as the alpha and lambda parameters are considerably high, thus augmenting the penalty terms.

Table 2. Alpha and Lambda (Regularization Parameters) of E-net regression for GDP and inflation analysis with UMPTs and Interest Rates (source: prepared by the authors)

Sample	Alpha	Lambda
GDP (UMPTs + interest rates)	0.3	0.6
GDP (Interest rates)	0.4	0.6
GDP (UMPTs)	0.9	0.2
Inflation (UMPTs + interest rates)	0.1	0.1
Inflation (Interest rates)	0.2	0.2
Inflation (UMPTs)	0.4	0.1

In Table 3 we present the adjusted R-square values for all regressions performed in our study. One notable observation is the absence of P-values, t-stats, and F-stats. This is attributable to the complexity of calculating these values for Elastic Net regression. While these values could be computed for the Ordinary Least Squares (OLS) regression, we opted not to include them to maintain the robustness of our research. The Elastic Net regression does not provide a straightforward method for computing these values, unlike the OLS method. Although there have been attempts to calculate these values, they are not trivial (Lockhart et al., 2014; Tabassum & Ollila, 2017; Horel & Giesecke, 2020), and no existing programming languages, including Python and R, offer functions for this purpose. This complexity is beyond the scope of our research.

Secondly, we perform an OLS regression as a basic model and then apply Elastic Net regression as our primary working model. From the OLS regression, we observed that the adjusted R-squared values for UMPTs and interest rates, a combination of unconventional and conventional monetary policy tools, were significantly high for both GDP (GDP means growth rate here) (0.62) and inflation rate (0.79). However, when applying Elastic Net regression, we found that only the adjusted R-squared value for the inflation rate remained high (0.64), while for GDP, it dropped significantly to 0.13. This is a positive indication, suggesting that unnecessary coefficients, likely suffering from multicollinearity, were reduced to zero. These findings align with economic theory, which posits that the primary objective of contemporary monetary policy is inflation targeting, not GDP targeting. It is therefore logical that inflation would be more responsive to monetary policy, while GDP would be influenced more indirectly. This is precisely what we observed from the Elastic Net regression.

Table 3. OLS and E-net regression statistics for GDP and inflation (source: prepared by the authors)

Sample	OLS	E-net
GDP (UMPTs +)	0.6208	0.1344
GDP (Interests)	0.3763	0.1122
GDP (UMPTs)	0.2971	0.137
Inflation (UMPTs +)	0.7897	0.6356
Inflation (Interests)	0.4705	0.4146
Inflation (UMPTs)	0.4942	0.3372
Average for GDP	0.4267	0.1323
Average for Inflation	0.6133	0.4627

In our statistical hypothesis testing, we used simulations and MBB methods. The results of these simulations are presented in Table 4. To explicate the contents of the table, the 'sample' column represents the samples on which MBB was performed. We constructed four distributions. One such distribution measures the difference in R-squared between different samples. For instance, the distribution titled 'Inflation ((UMPTs+Interest rates)-Interest rates)' measures the differences in the adjusted R square of inflation, UMPTs, and interest rates, and the adjusted R square of inflation and interest rate alone.

Table 4. 5% confidence intervals for GDP growth rate and inflation after applying MBB with UMPTs and interest rates (source: prepared by the authors)

Sample	5% confidence intervals (Percentile method)
Inflation ((UMPTs+ Interest rates) – interest rates)	(0.03, 0.34)
Inflation (UMPTs alone)	(0.052, 0.36)
GDP growth rate ((UMPTs + interest rates) – interest rates)	(–0.01, 0.04)
GDP growth rate (UMPTs alone)	(–0.12, 0.19)

From Table 4, it is evident that for both samples in both distributions related to the inflation rate, the confidence intervals do not include zero. This implies that the adjusted R-squared is indeed non-zero. Conversely, both distributions for the GDP growth rate include zero. Therefore, from the MBB simulations, we cannot conclude that the adjusted R-squared for these is non-zero.

These findings align well with economic theory and the mandate of the ECB, which primarily targets inflation and not GDP growth. GDP growth is considered a secondary, indirect economic indicator influenced by the monetary policy of the ECB. We are gratified that our results align with both economic theory and the mandate of the ECB.

In Table 5, we present the coefficients derived from the elastic net regression. It is observed that for the GDP growth rate, most coefficients are converging towards zero, except the coefficients for the Marginal Lending Facility and the Asset Purchase Programme. This suggests, within the framework of our research, that the GDP growth rate is primarily influenced by these two factors. Contrastingly, for inflation, a majority of the coefficients do not converge to zero, indicating their statistical importance. It is crucial to note that, in the context of elastic net regression, we are referring to their importance rather than statistical significance, as p values are not provided in this analysis. Interestingly, the coefficient for the Pandemic Emergency Purchase Programme (PEPP) has been reduced to zero, implying that this particular unconventional monetary policy tool does not statistically influence the inflation rate, according to our analysis. This investigation underscores the nuanced impacts of various unconventional monetary policy tools on key economic indicators, providing valuable information to policymakers and academic scholars. More research is warranted to continue exploring these complex relationships.

Table 5. Elastic-Net regression coefficients for inflation and GDP growth rate across various monetary policy tools (source: prepared by the authors)

Tool name	Inflation	GDP growth rate
Deposit facility	0.124843626	0
Main refinancing operations	0.264186179	0
Marginal lending facility	0.161842813	–0.33459365
LTROs	–0.128952196	0
Asset Purchase Programme	0.171577897	0.174875824
TLTROs	–0.559421718	0
PEPP	0	0
TLTRO II	–0.008699635	0
TLTRO III	0.014712866	0
SMP	0.632258195	0

In the subsequent phase of our research, we employed the ARIMA process to the residuals that remained after applying the Elastic Net regression. This step was only for the UMPTs and interest rate models, both for the inflation rate and the GDP growth rate. The residuals from these models were utilised in the ARIMA process.

For the inflation rate model, we used an ARIMA(4,1,3) For the GDP growth rate, we ARIMA(5,0,5) model. Following this, we conducted a robustness check of our model. A residual check was performed after the ARIMA process.

The results of the statistical tests conducted on the residuals are presented in Table 6. We examine the mean, autocorrelation, normality, and homoscedasticity of the residuals. For the autocorrelation test, we used the Ljung-Box test and tested autocorrelation up to the 10th lag. The results, including the p-values, are provided in the Table 6. For the normality test, we used the Shapiro-Wilk test, and the p-values are included in the Table 6. Lastly, for the homoscedasticity test, we used the ARCH test, and the p-values are also provided in the Table 6.

From the Table 6, we observe that the mean of the inflation rate is approximately zero. The LjungBox test indicates that there is no autocorrelation up to the 10th lag. The Shapiro-Wilk test reveals that the residuals are normally distributed as the p-value is 0.62. The ARCH test value is 0.72, suggesting that the residuals are homoscedastic. In terms of the GDP growth rate, the mean is nearly zero, which we consider to be zero. The Box-Pierce test result is 0.79, indicating that there is no autocorrelation up to the 10th lag. However, the Shapiro-Wilk test and the ARCH test have very small p-values, suggesting that the residuals are not normally distributed and are not homoscedastic.

Table 6. Diagnostic test results of residuals for Inflation and GDP growth rate (source: prepared by the authors)

Test name	Inflation	GDP growth rate
Mean	0.002	–0.009
Ljungbox test	0.98	0.79
Shapiro-Wilk test	0.62	4.87E-12
ARCH test	0.72	8.29E-14

Following the robustness check and inspection of residuals, we can infer that the model is well-suited for inflation data. However, there are certain issues when it comes to GDP growth rate data. This does not necessarily cast doubt on the results obtained from the elastic net regression. It merely suggests that if we intend to use this model and these variables to forecast the GDP growth rate, we should be prepared for less precise confidence intervals.

Figures 1 and 2 provide visual representations of the fitted values from the Elastic Net model with the ARIMA residuals. These fitted values pertain to both inflation data and the

Figure 1. Elastic Net model's fitted vs actual values for inflation for the training set (2008–2020) (source: prepared by the authors)

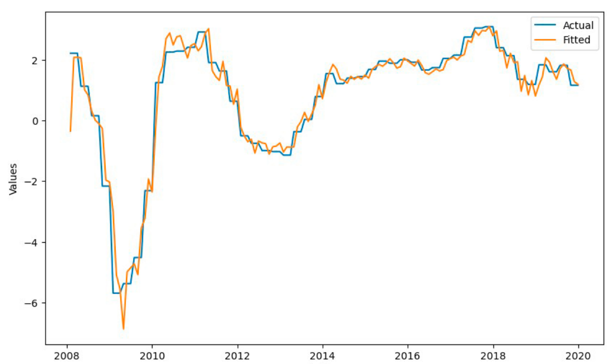

Figure 2. Elastic Net model fitted vs. actual values for GDP growth rate for the training set (2008–2020) (source: prepared by the authors)

GDP growth rate and are based on the training set. A close examination of these Figures 1 and 2 reveals a strong alignment between the fitted and actual values, suggesting that the model performs well on the training set. Notably, the model successfully captures the significant downturns following the Great Recession in both inflation and GDP growth rate data. It also accurately reflects the subsequent recovery, demonstrating its effectiveness in stable and unstable economic environments, such as the Great Recession and the debt crisis.

Figures 3 and 4 offer a visual examination of the predicted data of the test set. The model appears to perform well for both inflation rate and GDP growth rate data. While the GDP growth rate data exhibit more noise and unnecessary fluctuations in the forecasted data compared to the actual data, the overall fit is satisfactory. From a visual standpoint, the model performs admirably with the test set of unknown data, indicating a good generalisation. However, visual inspection is not a robust statistical technique for evaluating forecast accuracy. Therefore, we employed the Mean Absolute Scaled Error (MASE) to measure our model's forecasting performance.

For the GDP growth rate data, the MASE was 4.31. This metric was chosen because of its simplicity of calculation, scale-independence, and ability to compare our model with basic naive models. A MASE of 4.31 suggests that the forecasting accuracy of our model is significantly worse than that of naive methods, despite its complexity. This indicates that this model may not be suitable for forecasting GDP growth rate data.

In contrast, the MASE for the inflation rate data was 1.56, indicating better performance than the GDP growth rate data, but still worse than a naive model. Given the simplicity of the naive model, it may not be necessary to use our complex model to forecast inflation or GDP growth rate data.

Our primary discovery indicates a substantial influence of the UMPTs used by the ECB on inflation within the euro area. However, the relationship between the GDP growth rate and UMPTs is not as linear. We observe that the adjusted R-squared value for the correlation between UMPTs and the GDP growth rate is relatively small. When conducting hypothesis testing using the MBB method on this sample, we determined that the adjusted R-squared value is not significantly different from zero.

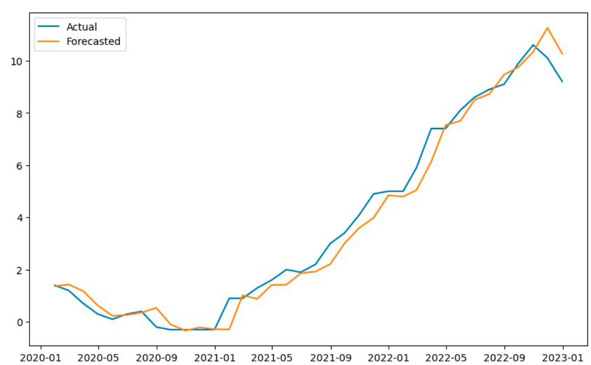

Figure 3. Elastic Net model's forecasted vs. actual inflation rate (2020 Q1 – 2023 Q1) (source: prepared by the authors)

This outcome substantiates our initial hypothesis that UMPTs serve as an effective instrument for achieving inflation targets in the euro area. Furthermore, our research suggests that the combined application of UMPTs and interest rates exerts a more potent impact on inflation than the isolated use of either interest rates or UMPTs. This finding implies that UMPTs and interest rates operate through distinct transmission mechanisms and mutually enhance their influence on macroeconomic variables.

Our research significantly extends the theoretical framework initially proposed by Clarida et al. (1999) and later refined by Woodford and Walsh (2005). This framework, characterised by the Taylor rule, uses interest rates as the primary instrument. Our robust findings and methodology provide a solid foundation for the inclusion of monetary policy-building models in future research. Previous attempts to construct DSGE models for monetary policy have included UMPTs without fully understanding the relationship and impact of these models on key macroeconomic indicators. Our research provides comprehensive and robust foundations for the development of future DSGE models for monetary policy. Our work builds upon the research of Ouerk et al. (2020), Mouabbi and Sahuc (2019), Conti et al. (2017), Horvath and Voslarova (2017), Zabala and Prats (2020), de Haan et al. (2020), Mitchell and Pearce (2020), Ambler and Rumler (2019), Bottone and Rosolia (2019). These studies analyse unconventional monetary policy tools as a forecast for inflation and other vehicles. Our research sheds light on the strength of the relationship between unconventional monetary policy tools and macroeconomic indicators. This understanding will significantly influence the construction of upcoming DSGE models for monetary policy.

This investigation is part of a wider series of research projects that are aimed at building an all-encompassing DSGE model that accurately portrays contemporary monetary policy. Although the integration of additional variables could result in a more complex model, it would exceed the scope of this individual investigation. Consequently, we have opted to concentrate on these particular aspects to ensure a concentrated and manageable scope for our present research. Subsequent research within this series will encompass other contemporary monetary policy institutions and will take into account additional variables, such as cryptocurrency prices.

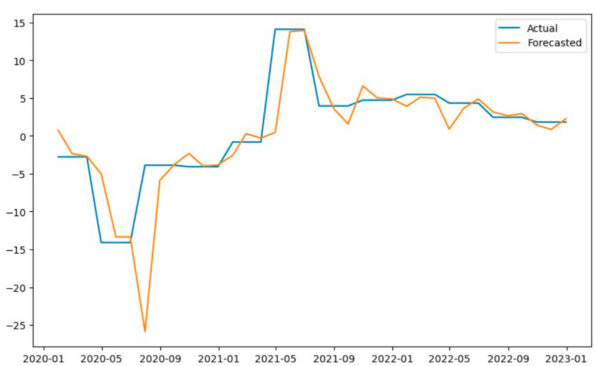

Figure 4. Elastic Net model's forecasted vs. actual GDP growth rate (2020 Q1 – 2023 Q1) (source: prepared by the authors)

5. Conclusions

This research aimed to examine the influence of UMPTs employed by the ECB on the inflation rate and GDP growth rate within the euro area. Motivated by the principles of the Taylor rule, we employed an analytical framework, utilising elastic net regression to dive into the relationship between UMPTs and economic indicators, gauged through adjusted R-squared metrics.

Through the construction of six diverse samples, we examined various scenarios, including combined monetary policy tools, individual policy components, and UMPTs in isolation. Our findings revealed nuanced insights into the efficacy of these policies, with substantial declines in adjusted R-squared values, observed after the application of regularisation techniques, particularly evident in GDP growth rate samples.

The analysis reveals a significant shift in the relationship between GDP and inflation in the context of UMPTs. The adjusted average R-square for GDP showed a substantial decrease, indicating a weaker correlation over time. On the other hand, the impact on inflation, although still noteworthy, experienced a less pronounced reduction. This suggests that inflation remains more closely tied to these variables.

The confidence intervals further substantiate these findings, pointing to a significant influence of UMPTs on inflation, especially when considered in conjunction with interest rates. This underscores the importance of considering multiple economic factors when analysing the effects of UMPTs.

Our findings have implications for monetary policymakers and academic scholars, emphasising the need for continued research on contemporary monetary policy frameworks. While our study focused on the euro area, future research efforts should expand to encompass other major economies, such as the USA, and explore emerging digital currencies' impact.

This investigation forms part of a broader research series aimed at building a comprehensive DSGE model. While integrating additional variables, including cryptocurrency prices, holds promise, it exceeds the scope of this study. Subsequent research within this series will incorporate additional variables and consider diverse monetary policy institutions, offering a more nuanced understanding of contemporary monetary policy dynamics.

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