Sectoral Responses to ECB Rate Hikes: Impact on GDP and Wages

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Abstract

This paper explores the heterogeneous impact of the interest rate hikes introduced by the European Central Bank in July 2022, examining how differences in the sectoral composition of Eurozone countries influence their economic responses to monetary tightening: the analysis investigates whether the relative weight of the primary, secondary, and tertiary sectors affects the extent to which each country is exposed to and influenced by changes in interest rates. Drawing on macroeconomic data from Eurostat and the ECB, and employing a Difference-in-Differences (DiD) approach, the study evaluates the effects of the policy on both GDP and wages, where countries are grouped into treatment and control categories based on the predominance of each sector in their economy, measured as the share of sectoral value added over total GDP.

The findings suggest that countries with a strong secondary sector appear to be more resilient to interest rate hikes, showing significant wage increases and no substantial decline in output; in contrast, economies more dependent on the primary or tertiary sectors tend to suffer a marked drop in GDP without experiencing any meaningful wage growth.

However, the analysis also acknowledges some limitations, particularly concerning the assumption of treatment participation in the primary and tertiary sectors, which may not have been fully exposed to the effects of monetary policy.

1 INTRODUCTION: A LITERATURE REVIEW

In response to an unprecedented surge in inflation, the European Central Bank (ECB) initiated a series of interest rate hikes in July 2022, marking the first increase in over a decade. This decision was driven by multiple factors that threatened price stability and economic equilibrium within the Eurozone [1].

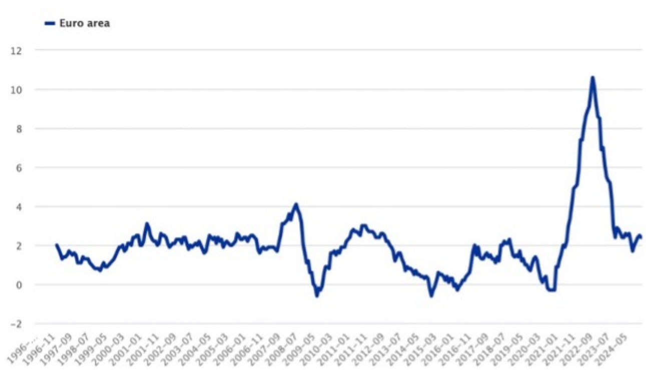

Figure 1: Inflation Rate (year on year percentage)

Throughout 2022, inflation escalated sharply, reaching an annual average of 8.4%, with a peak of 10.6% in October. This was a significant deviation from the ECB's 2% inflation target, fueled primarily by a dramatic increase in energy prices following the Russian invasion of Ukraine, in food prices due to disruptions in global supply chains and in prices in general due to a strong post-pandemic demand, particularly in the service sector.

The increase in interest rates represents the main tool available to the ECB to bring inflation back to the 2% target. When the central bank raises interest rates, the cost of credit for households and businesses increases, making loans more expensive, leading to a reduction in consumption and investment, with a consequent decline in

[1] European Central Bank, 2022

aggregate demand: if demand decreases, businesses find it more difficult to raise prices, thereby helping to contain inflation. Furthermore, higher interest rates encourage saving over spending, as returns on deposits and bonds increase, further limiting consumer spending and helping to reduce price pressures. Another key effect concerns the exchange rate of the euro: with higher rates, the euro tends to appreciate, making imports cheaper and helping to mitigate imported inflation, particularly for energy and raw materials.

However, the effectiveness of this monetary policy varies depending on the economic structure of each country and sector: some sectors, such as real estate and manufacturing, are more affected by the increased cost of capital, while others, such as the financial sector, may benefit from higher profit margins.

The heterogeneity of the impacts of monetary policy was highlighted in the Federal Reserve paper *"Country-Specific Effects of Euro-Area Monetary Policy: The Role of Sectoral Differences"*, which analyzes how ECB monetary policy affects the economies of Eurozone countries differently based on their sectoral composition. Using macroeconomic data, the authors evaluated how changes in interest rates influence real GDP and the value added in the manufacturing and services sectors, finding that a one-percentage-point increase in the ECB's monetary policy rate significantly reduces the real GDP of the Eurozone, with more pronounced effects in the manufacturing sector than in services: the results indicate that countries with a larger share of manufacturing experience a more severe economic contraction following an interest rate hike, whereas a greater presence of the services sector tends to mitigate this effect.

To further explore this topic, the analysis will be extended to assess the sectoral effects of monetary tightening, focusing on the three macroeconomic sectors in each Eurozone country: primary, secondary, and tertiary. The objective is to evaluate how interest rate increases affect GDP and wages in these sectors, analyzing how a country's productive structure determines its sensitivity to monetary policy. Unlike the Federal Reserve study that focuses on the comparison between manufacturing and services, the following paper considers a broader classification of the economy, focusing on the primary, secondary, and tertiary sectors. Additionally, for each country, the ratio between the value added of each sector and national GDP will be calculated, allowing for the classification of countries based on the predominance of one of the three macro-sectors: in this way, it will be possible to identify which economies are primarily driven by the primary, secondary, or tertiary sector, capturing structural differences among Eurozone countries and analyzing how these sectors respond to monetary policy changes. From a methodological perspective, a *Difference-in-Differences (DiD)* approach will be adopted instead of the *Local Projection (LP)* method, allowing for a comparison of the evolution of GDP and wages between sectors that are more and less exposed to interest rate hikes, isolating the effect of monetary policy with greater precision. The analysis will rely on macroeconomic and sectoral data, and the distinction between economies with a dominant primary, secondary, or tertiary sector will allow for an assessment of whether monetary policy has differentiated effects depending on the productive structure of each country and its reliance on specific economic sectors.

2 DATA

The data used in this analysis were obtained from **Eurostat** and the **European Central Bank database**.

The dataset consists of multiple tables, each corresponding to a specific economic indicator.

For the indicators *Employment*, *GDP*, *Wages*, and *Added Value*, each table includes the following columns:

Column	Description
Country	Names of the 20 countries belonging to the Euro-area, plus Euro-area aggregate value
Year	Year of observation (2010–2024)
Quarter	Quarter of the year (Q1, Q2, Q3, Q4)
Value	Numerical value of the indicator for the specific sector: millions for GDP and Added Value, thousands for Wages and Employment

Table 1: Structure of dataset tables by sector

For *Employment* and *Added Value*, there is a distinct table for each economic sector considered, which are *Agriculture, Forestry and Fishing*, *Construction*, *Industry (excluding construction)*, *Manufacturing* and *Wholesale and retail trade, transport, accommodation, and food service activities.*

For the indicator *Inflation Rate*, each country has its table, with the value expressed as a month-on-month percentage change.

2.1 DATA PREPARATION

For the *Employment*, *GDP*, *Wages_and_Salaries*, and *Added_Value* tables, the same steps were applied to standardize the data:

1. Only the columns `geo`, `OBS_VALUE`, and `TIME_PERIOD` were retained.
2. The column `geo` was renamed to `Country`, and `OBS_VALUE` was renamed to `Value` to ensure consistency across all tables. Additionally, the Euro area was renamed from `Euro area _ 20 countries (from 2023)` to `Euroarea` for standardization.
3. The `TIME_PERIOD` column was divided into `Year` and `Quarter` to facilitate temporal analysis.
4. For Employment and Added_Value, sectors were grouped as follows:
   a) The primary sector includes only *Agriculture, Forestry and Fishing.*
   b) The secondary sector was created by merging the *Construction*, *Manufacturing*, and *Industry (excluding construction)* tables into a single dataset.
   c) The tertiary sector includes *Wholesale and retail trade, transport, accommodation, and food service activities.*

The *Inflation_Rate* table required a different treatment due to its distinct structure: before proceeding, a single table was obtained by merging all the tables of the individual countries, making each country a separate column with inflation rate values corresponding to specific dates. Therefore, the following restructuring steps were applied:

1. The column `Time` was split into two distinct columns: `Year` and `Quarter`.
2. A new column, `Country`, was created by gathering all country names originally used as column headers (translated from Italian into English).
3. A new column, `Value`, was generated to store the inflation rate values for each quarter and year, calculated as the quarterly average for each country.

The time period selection was applied uniformly across all datasets: only data from 2010 onward were retained and 2020 was excluded to avoid distortions caused by extraordinary events (Covid). Additionally, all rows related to Q4 of 2024 and 2025 were removed, as only a few records contained these data, and a completeness check was performed to ensure that all countries had data for each quarter in the selected period.

To classify the Eurozone countries based on the relative weight of different economic sectors (primary, secondary, and tertiary), the `ranking_primary`, `ranking_secondary`, and `ranking_tertiary` tables were created by applying the following steps:

1. Data from Q1 2021 to Q2 2022 were selected, as the objective was to analyze the economic conditions of Eurozone countries around the period when the European Central Bank (ECB) introduced the new interest rate in 2022. Aggregate Euroarea data were excluded, retaining only individual country data.
2. For each sector (primary, secondary, and tertiary), the `Added_Value` datasets were merged with the `GDP` dataset based on `Country`, `Year`, and `Quarter`. After merging, the ratio between the sector's Added Value and total GDP was calculated for each country and quarter as follows:

   $$\text{ratio} = \frac{\text{Added Value}_{\text{Sector}}}{\text{GDP}_{\text{Value}}}$$

   This calculation was performed separately for each sector.
3. Once the quarterly sector/GDP ratios were calculated, the average ratio (`avg_ratio`) for each country was computed:

   $$\text{avg\_ratio} = \frac{\sum \text{quarterly ratios}}{\text{number of quarters considered}}$$

Each resulting ranking table contains two columns: `Country` and `avg_ratio`.

3 DESCRIPTIVE STATISTIC

The ranking table values indicate the relative importance of each sector in the national economy, highlighting how agriculture, industry, and services have different weights across Eurozone countries.

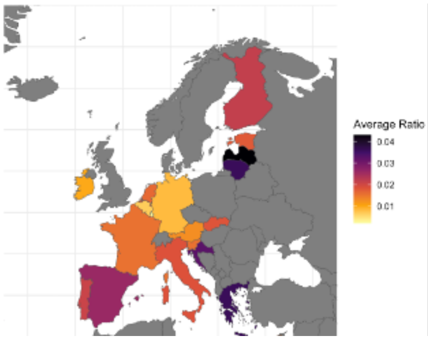

Figure 2: Primary Sector

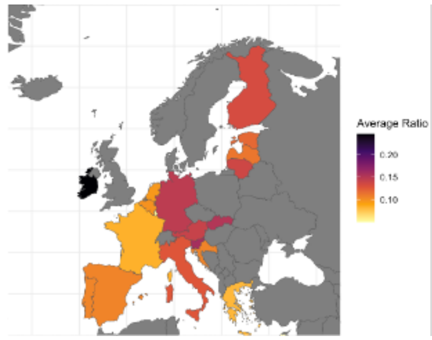

Figure 3: Secondary Sector

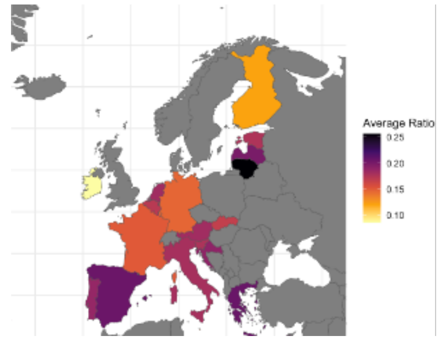

Figure 4: Tertiary Sector

The primary sector, Figure 2, accounts for an average of 1.89% of GDP in Eurozone countries, confirming its lower significance compared to other economic sectors. The values range from a minimum of 0.20% to a maximum of 4.30%, with the highest percentages recorded in Latvia, Greece, Lithuania, and Croatia (in Eastern and Southern Europe), while the lowest values are observed in Luxembourg, the Netherlands, and Germany (in Western Europe). This significant variation among countries indicates that some economies still maintain a strong agricultural role, while others have shifted almost entirely towards industry and services.

The secondary sector, Figure 3, remains a key player in the European economy, with an average contribution of 11.54% to GDP. However, its importance varies significantly between countries, with values ranging from 5.00% to 24.59%: the countries with the highest share are Ireland, Slovenia, Slovakia, and Germany, which maintain a strong industrial and manufacturing base that continues to be a fundamental pillar of their economies. In contrast, France, the Netherlands, and Belgium show the lowest shares, reflecting a shift from industry towards services.

The tertiary sector, Figure 4, has become the dominant economic force in many European countries, with an average share of 17.36% of GDP. Some nations, particularly Lithuania, Greece, Spain, and Cyprus, rely heavily on services, with the sector contributing up to 25.60% of GDP, largely fueled by tourism and trade. Meanwhile, Germany, Slovakia, and Ireland register lower shares, down to 8.57%, as their economies remain more oriented towards industry and manufacturing.

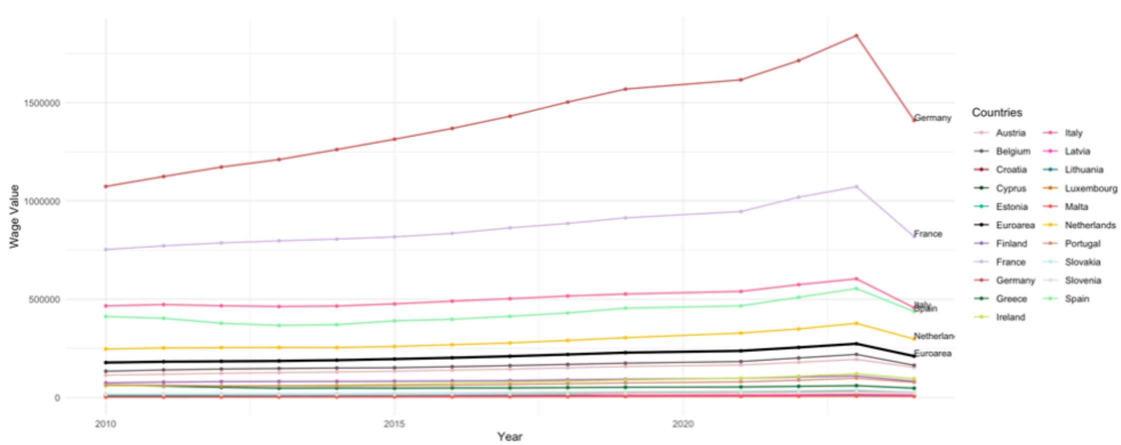

Figure 5: Wages Trend by Country

In Figure 5, the wage trend clearly mirrors the GDP trend previously analyzed: in heavily industrialized countries like Germany, wages experienced a significant decline after 2022, consistent with the observed drop in GDP. On the other hand, countries with a larger share of the tertiary sector, such as Italy, display a more stable wage trajectory or a less pronounced decline. This suggests that economies relying more on services and tourism were able to better absorb the impact of rising interest rates, experiencing less volatility in wage levels compared to industrial-oriented economies.

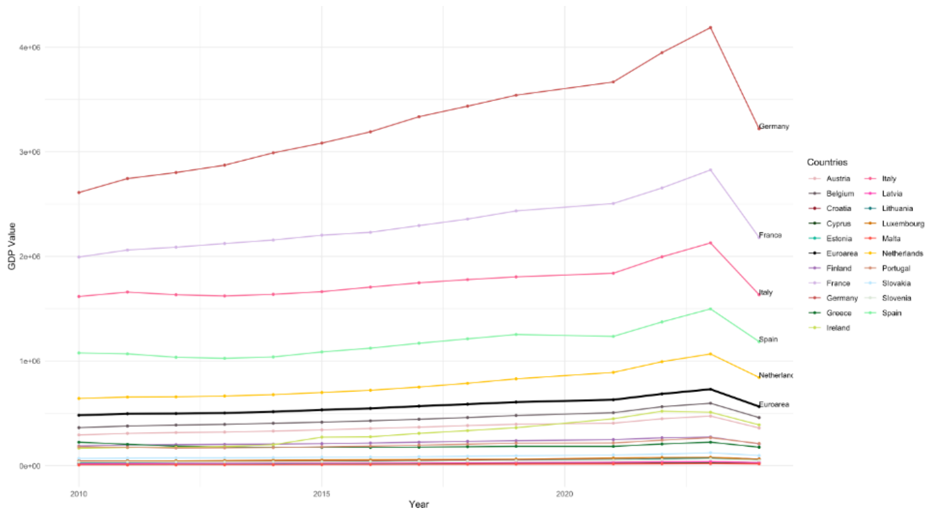

Figure 6: GDP Trend by Country

In Figure 6, the GDP trend for most Eurozone countries follows an increasing trajectory up until 2022, with Germany clearly emerging as the economic leader in absolute terms. After 2022, looking at the Euroarea average, we observe a downward reversal of this trend: countries like Germany experienced a notable decline, while countries like Italy experienced a less marked drop in GDP compared to Germany. This suggests that economies more oriented towards the tertiary sector, such as Italy, have better absorbed the impact of rising interest rates compared to those heavily reliant on industry, such as Germany.

4 EMPIRICAL STRATEGY

The goal of this project is to analyze whether the increase in the interest rate applied by the European Central Bank (ECB) starting in July 2022 led to different changes in GDP and wages across various sectors, using the Difference in Differences (DiD) methodology. To achieve this, the first step involved dividing the Eurozone countries into treatment and control groups for each sector. This classification was based on a ranking system, the calculation of which was briefly explained in the data preparation section. Specifically:

- Countries above the 75th percentile of the ranking were assigned to the treatment group, with a value of 1.
- Countries below the 25th percentile of the ranking were assigned to the control group, with a value of 0.

This method ensured that for each sector, there were a total of 10 countries analyzed: 5 in the treatment group and 5 in the control group. This setup allows for a clear comparison of the effects across the two groups within each sector. Below, the countries included in each group for each sector are shown.

Group	Countries
Treatment (Top 25%)	Latvia, Greece, Lithuania, Croatia, Spain
Control (Bottom 25%)	Ireland, Germany, Malta, Belgium, Luxembourg

Table 2: Primary Sector

Group	Countries
Treatment (Top 25%)	Ireland, Slovenia, Slovakia, Germany, Austria
Control (Bottom 25%)	France, Greece, Malta, Cyprus, Luxembourg

Table 3: Secondary Sector

Group	Countries
Treatment (Top 25%)	Lithuania, Greece, Spain, Cyprus, Latvia
Control (Bottom 25%)	Luxembourg, Germany, Malta, Finland, Ireland

Table 4: Tertiary Sector

For each DiD model, the underlying assumptions and the robustness of the methodology were thoroughly examined to ensure the reliability and validity of the results. For those interested, these checks can be found in Appendix A and Appendix B, respectively. 7 8

4.1 DIFFERENCE-IN-DIFFERENCES FRAMEWORK

The DiD methodology provides a robust framework for isolating the treatment effect, taking into account temporal variation and the difference between the treatment and control groups. The model specification is based on a set of key variables, including the treatment variable, the post-intervention period, and a series of control variables, such as employment and inflation, to obtain robust and accurate estimates of the effects. The baseline DiD model is specified as

$$\log(Y_{ist}) = \beta_0 + \beta_1 \text{Treatment}_{is} + \beta_2 \text{Post}_{ts} + \beta_3 (\text{Treatment}_{is} \times \text{Post}_{ts}) + \mathbf{X}_{ist}\boldsymbol{\gamma} + \alpha_i + \lambda_t + \varepsilon_{ist}, \tag{1}$$

where

- $\log(Y_{ist})$: This is our main outcome, representing the logarithm of GDP or wages for country i, sector s, at time t. The log transformation is useful for interpreting percentage changes in the dependent variable, facilitating economic interpretation.
- Treatment_{is}: A binary variable indicating whether country i belongs to the treatment group (1) or the control group (0).
- Post_{ts}: Another binary variable indicating whether the observation is after the treatment (1, if the period is post-July 2022) or before the treatment (0, if the period is prior).
- $\text{Treatment}_{is} \times \text{Post}_{ts}$: This interaction term, denoted by β_3, captures the causal effect of the ECB intervention. It measures how the interest rate increase affected the outcome (GDP or wages) in the treated countries relative to the control group during the post-treatment period. This coefficient is key to understanding sector-specific responses to the policy, as it isolates the differential change attributable to the treatment.
- $\mathbf{X}_{ist}$: A vector of control variables, such as employment and inflation rate, are included in the model to account for other factors that might influence the dependent variables. Also these variables, as the outcome, are transformed into log.
- α_i: Country fixed effects, which capture unobserved but time-invariant characteristics for each country, such as the economic structure and other national peculiarities.
- λ_t: Time fixed effects, which control for factors that change over time at a common level for all countries, such as unobserved time-specific factors.
- ϵ_{ist}: The error term, which captures all other unobserved factors that might influence the dependent variable

In summary, the described DiD model provides a solid framework for examining the differences in the effect of the interest rate hike across countries and sectors, enabling a rigorous and reliable analysis of the economic impacts of the ECB's intervention.

5 EMPIRICAL RESULTS

5.1 IMPACT OF ECB POLICY ON GDP

Variable	Primary	Secondary	Tertiary
intercept	11.082***	7.603***	4.386***
treatment	0.831***	3.307***	0.0619
post	0.730***	0.608***	0.540***
employment	0.059	0.039***	0.807***
inflation	0.014***	0.011***	0.021***
post:treatment	-0.083**	0.027.	-0.075**

Table 5: Coefficients for DiD estimates and their significants

In the pre-treatment period, the average GDP of the control group is significantly higher in the primary sector (11.082), and the treatment variable is also significant at the 1% level in both the primary (0.831***) and secondary sectors (3.307***), indicating that the treated groups already exhibited higher GDP levels before the intervention. In contrast, in the tertiary sector, the treatment coefficient is low and not statistically significant (0.0619), suggesting good initial comparability between treated and control groups.

Following the intervention, all three sectors experience a general increase in GDP, regardless of treatment status. The post coefficients are positive and highly significant across the board (0.730*** in the primary sector, 0.608*** in the secondary, and 0.540*** in the tertiary), indicating a common upward trend over time that affects the entire economy and must be accounted for when isolating the effect of the treatment itself.

Among the control variables included in the model, Employment and Inflation exhibit sector-specific effects on GDP:

- In the *tertiary* sector, Employment has a particularly strong and statistically significant impact on GDP, with a coefficient (0.807***) indicating that an increase in employment is strongly associated with GDP growth, making it a key driver of economic performance in this sector. Inflation also shows a positive and significant relationship (0.021***), indicating that moderate price increases tend to be accompanied by economic expansion, possibly reflecting growing demand or nominal effects on output.
- In the *secondary* sector, both Employment (0.039***) and Inflation (0.011***) have a positive and statistically significant association with GDP, although the magnitudes of their effects are smaller than in the tertiary sector, suggesting that these factors play a more moderate role in driving growth in the industrial and manufacturing sectors.
- In the *primary* sector, Employment does not have a statistically significant impact on GDP, while inflation maintains a small but statistically significant positive effect (0.014***), suggesting that even in this sector, moderate price increases are associated with GDP growth.

The results of `post:treatment` show that the impact is negative and statistically significant in both the primary (-0.083, **) and tertiary sectors (-0.075,), so in these two sectors the treatment led to a clear reduction in GDP, with the statistical significance suggesting that these effects are not due to random variation: the treatment had a real and measurable negative impact on economic performance in both agriculture and services.
In contrast, in the secondary sector, the estimated effect is slightly positive (0.027), suggesting a possible increase in GDP following the treatment. However, this result is only marginally significant (.), meaning that the effect could be due to chance and should therefore be interpreted with caution.

5.2 IMPACT OF ECB POLICY ON WAGES

Variable	Primary	Secondary	Tertiary
intercept	10.258*	6.559*	5.254*
treatment	1.044*	3.397*	0.375*
post	-0.003	-0.007	-0.018
employment	-0.032	0.026*	0.302**
inflation	0.098*	0.057*	0.124*
post:treatment	0.029	0.028*	0.027

Table 6: Coefficients for DiD estimates and their significants

In all sectors the intercept is significant, but the value decreases from the primary sector (10.258*) to the tertiary sector (5.254*): these values indicate that, all else being equal, the primary sector starts from a higher average level compared to the other two sectors.
Moreover, before the treatment, in all three sectors, the wages in the treatment group were consistently higher than those in the control group, with the difference being significantly greater in the secondary sector (3.397*) and smaller in the primary and tertiary sectors (1.044* and 0.375*).

There is no significant variation in the control group between the pre- and post-treatment periods, as the coefficients in all three sectors are not statistically significant: this suggests that the changes observed in the dependent variable are not due to external factors affecting all groups, but are specific to the effect of the treatment.
Among the control variables included in the model, Employment and Inflation exhibit sector-specific effects on wages:

- In the *primary*, the coefficient is negative and not significant (-0.032), suggesting that employment does not have a significant impact on the dependent variable. Regarding inflation, the coefficient is positive and significant (0.098*), indicating that an increase in inflation is associated with an increase in the dependent variable in the primary sector.
- In the *secondary* and *tertiary* sectors, employment has a positive and significant effect on the dependent variable (0.026* and 0.302**, respectively), with a notably stronger impact in the tertiary sector. Inflation also shows a positive and significant effect in both sectors (0.057* and 0.124*), although the magnitude is somewhat lower than in the primary sector.

From the analysis of the various outputs, it can be deduced that the central variable of the Difference-in-Differences analysis, namely post*treatment, is statistically significant only in the secondary sector and is positive (0.028*). This means that the wages in the treatment group countries have increased compared to those in the control group. This relevance is not observed in the primary and tertiary sectors, where, despite having coefficients similar to the secondary sector (0.029 and 0.027), these are not statistically significant enough to prove the effect of the treatment.

6 CONCLUSION

The effectiveness and impact of the ECB's monetary policy are not uniform across Eurozone countries, but vary significantly depending on the sectoral composition of each economy: countries with a strong presence of the secondary sector may be better able to absorb the effects of interest rate hikes, whereas those more reliant on the primary or tertiary sectors tend to be more negatively affected in terms of GDP and do not benefit from wage increases.
However, an important limitation of the analysis concerns the fact that, with respect to GDP, the assumption of participation in the treatment may not be fully satisfied in the primary and tertiary sectors. In other words, these sectors may not have been directly or fully exposed to the effects of monetary tightening, which weakens the causal identification of the treatment effect in the Difference-in-Differences framework. This limitation suggests that results for these sectors should be interpreted with caution and highlights the need for further investigation, possibly through alternative approaches that account for varying degrees of sectoral exposure to monetary policy.

7 APPENDIX A

This Appendix provides comprehensive diagnostics that test the core identification assumptions.

7.1 COMMON TREND ASSUMPTION

A key identifying assumption in difference-in-differences (DiD) analyses is the *parallel trends assumption*, which states that, in the absence of the treatment, the treated and control groups would have followed the same trajectory over time: in other words, any differences in the outcome variable after the intervention can be attributed to the treatment, provided that the groups were evolving similarly beforehand.
Verifying that the pre-treatment trends are parallel is crucial to ensure that the estimated treatment effects are not driven by pre-existing differences in trends between the groups.

7.1.1 VISUAL INSPECTION

Starting with **GDP** as the outcome variable, a preliminary support for the parallel trend assumption is shown in the visual inspection of the pre-treatment trends in Figures 7, 8, and 9, the trajectories of the treatment and control groups appear broadly similar across the primary, secondary, and tertiary sectors.

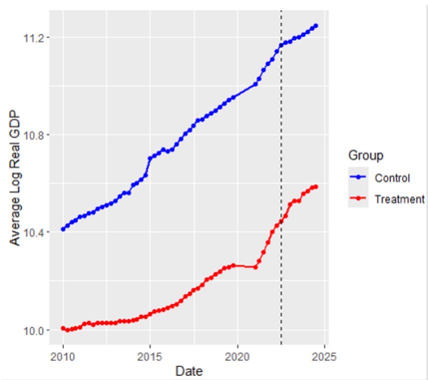

Figure 7: Primary Sector

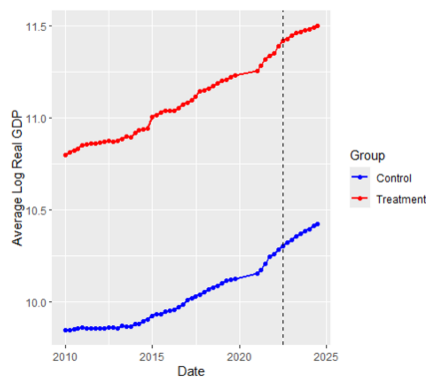

Figure 8: Secondary Sector

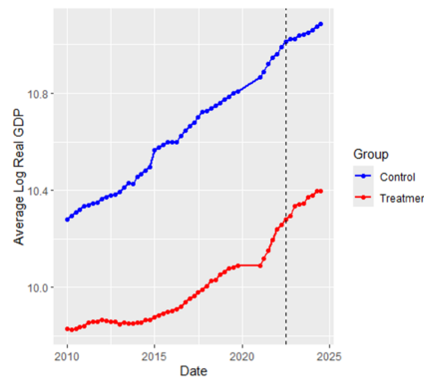

Figure 9: Tertiary Sector

Similarly, for the variable **Wages** used as the outcome, it can be observed that the trajectories of the control and treatment groups in the pre-treatment period are nearly identical across all three sectors, as it is shown in the following Figures 10, 11 and 12:

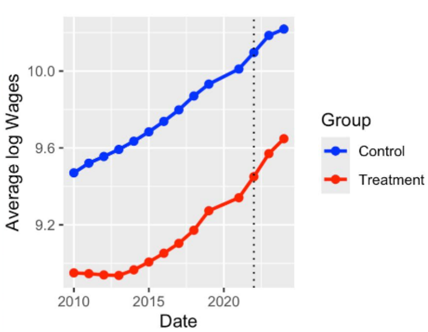

Figure 10: Primary Sector

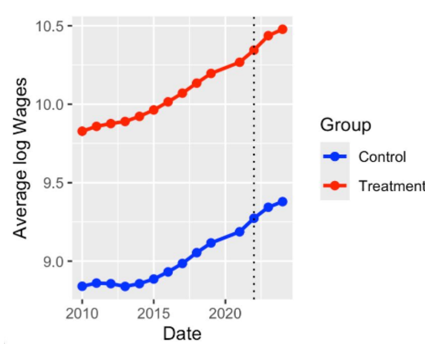

Figure 11: Secondary Sector

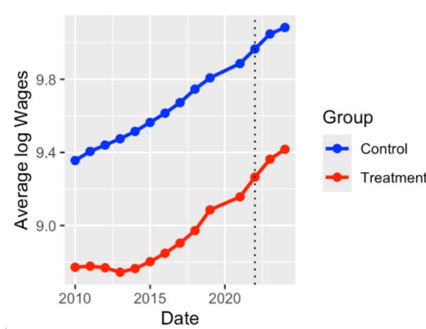

Figure 12: Tertiary Sector

7.1.2 FALSIFICATION (PLACEBO) TEST

To strengthen the credibility of the identification strategy, a placebo test is conducted by artificially assigning the policy intervention to an earlier period, specifically to 2021-Q3 (when no actual policy took place): this approach helps assess whether the estimated treatment effect might be driven by pre-existing differences between the treatment and control groups.

The model is estimated as:

$$\ln(Y_{its}) = \alpha + \beta_1 \cdot (\text{treatment}_{is} \times \text{placebo\_post}_{ts}) + \gamma_i X_{its} + \varepsilon_{its} \tag{2}$$

where Y_{its} is the outcome variable GDP or Wage, $\texttt{placebo\_post}_{ts}$ is a binary indicator equal to 1 from 2021-Q3 onward and to 0 otherwise, and X_{its} includes control variables such as employment and inflation rate.

If the coefficient β_1 on the interaction term is statistically insignificant, it indicates that no treatment effect is detected prior to the actual intervention, thereby supporting the parallel trends assumption, while a significant effect would suggest possible violations of the identification strategy.

The placebo test results for the outcome variable **GDP** confirm the absence of spurious treatment effects prior to the actual policy intervention. In all three sectors, the interaction term between the treatment indicator and the placebo post-intervention dummy is statistically insignificant: for the primary sector ($p = 0.463$), in the secondary sector ($p = 0.260$), and in the tertiary sector ($p = 0.563$). Similarly, when using **Wages** as the outcome variable, the interaction also remains statistically insignificant across all sectors with primary ($p = 0.71$), secondary ($p = 0.26$) and tertiary ($p = 0.71$).
These consistent findings across both placebo specifications indicates that the estimated treatment effects on the main outcomes are unlikely to be driven by pre-existing trends or omitted variable bias.

7.1.3 EVENT-STUDY DiD WITH CONTROLS

To further evaluate the parallel trend assumption, an event-study specification is estimated using the following regression model:

$$\ln(Y_{its}) = \alpha + \sum_{k \neq -1} \beta_k \cdot (\text{treatment}_{is} \times \text{event\_time}_{kts}) + \gamma_i X_{its} + \varepsilon_{its} \tag{3}$$

where Y_{its} denotes the outcome variables GDP or Wages, and X_{its} is a vector of control variables including employment and inflation rate. The variable $\texttt{event\_time}_{kts}$ captures the number of quarters relative to the treatment period (with $k = -1$, i.e. 2022-Q2, used as the reference period and thus omitted from the regression). Each coefficient β_k represents the estimated effect of the treatment at a specific point in time relative to the intervention.

The interaction terms between `treatment` and each value of `event_time` allow to trace the dynamic evolution of the treatment effect before and after the policy was implemented: non-significant coefficients in the pre-treatment periods (i.e., for $k < 0$) provide evidence that the treatment and control groups were following similar trends prior to the intervention, and that the policy was not anticipated.

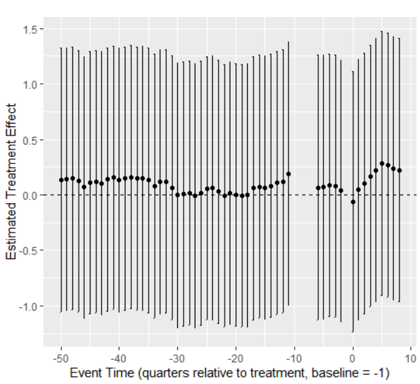

Figure 13: Primary Sector

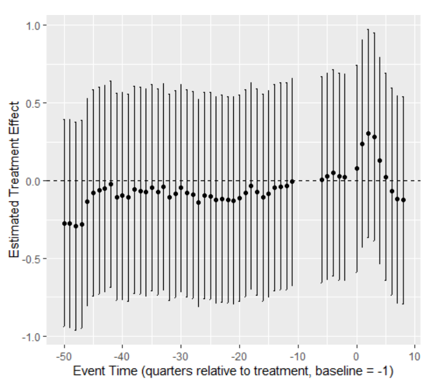

Figure 14: Secondary Sector

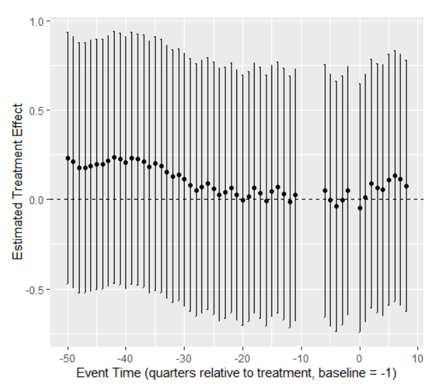

Figure 15: Tertiary Sector

For the outcome variable **GDP**, Figures 13 and 15 reveal no significant effects of the treatment on GDP in either the tertiary or primary sectors. In both cases, all post-treatment `treatment:event_time` interaction terms remain statistically insignificant (e.g. *tertiary sector*, time 0: -0.008, $p = 0.98$ or time +8: -0.027, $p = 0.92$; *primary sector*, time 0: 0.012, $p = 0.98$), indicating the absence of any causal impact following the intervention. Although the treatment variable itself is negative and significant in both models (*tertiary*: -0.62, $p = 0.002$; *primary*:

-1.27, $p < 0.001$), this reflects a persistent difference in levels between treated and control groups, rather than a divergence in post-treatment trends. For the secondary sector instead, Figure 14 shows that the treatment had no significant impact on GDP, as all post-treatment `treatment:event_time` coefficients are statistically insignificant (e.g. time+2: 0.23, $p = 0.34$ or time+8: -0.33, $p = 0.19$). The overall treatment effect is also not significant (-0.14, $p = 0.43$), indicating no level differences between treated and control groups.

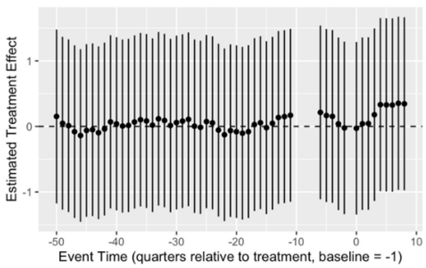

Figure 16: Primary Sector

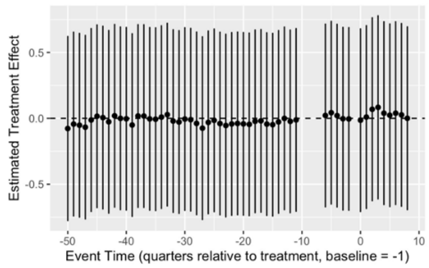

Figure 17: Secondary Sector

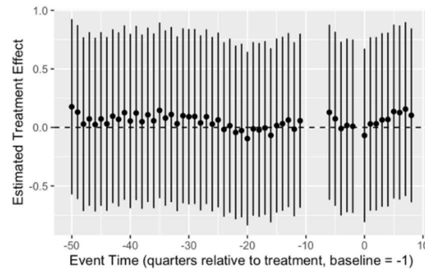

Figure 18: Tertiary Sector

For the outcome variable **Wages**, Figures 16, 17, and 18 reveal no significant effects of the treatment across any of the three sectors. In all cases, post-treatment `treatment:event_time` interaction terms are statistically insignificant, indicating the absence of a causal effect on wage dynamics following the intervention (e.g. *primary sector*, time 0: -0.028, $p = 0.97$; *secondary sector*, time +8: 0.001, $p = 0.999$; *tertiary sector*, time +8: 0.103, $p = 0.78$). Although the treatment coefficient is negative and statistically significant in the primary and tertiary sectors (*primary*: -2.40, $p < 0.001$; *tertiary*: -1.13, $p < 0.001$), it merely reflects a persistent level difference between treated and control groups, rather than a shift in post-intervention trends. In the secondary sector, no significant differences in either levels or trends are detected (-0.35, $p = 0.17$).

As with GDP, the insignificance of all pre-treatment interaction terms across sectors confirms the parallel trends assumption, thereby supporting the validity of the Difference-in-Differences identification strategy.

In conclusion, for both outcome variables — GDP and wages — the parallel trends assumption is satisfied, as evidenced by the insignificance of pre-treatment interactions, the visual inspection of parallel trends, and the lack of significant effects in the placebo test.

7.2 PARTICIPATION IN TREATMENT IS INDEPENDENT OF IDIOSYNCRATIC SHOCKS ASSUMPTION

A crucial aspect in verifying that the estimated model is based on solid foundations concerns the assumption that *participation in the treatment is independent of idiosyncratic shocks.* This assumption implies that an individual's decision to participate in a treatment is not influenced by unpredictable and individual-specific factors, such as random events or unforeseen circumstances, that could alter the outcomes and distort the relationship between the treatment and the observed outcomes. This allows for a more accurate estimation of the causal effect of the treatment, reducing the risk that the results are contaminated by unobservable variables or external effects not directly related to the treatment itself. Therefore, it represents a fundamental condition to ensure the validity and reliability of this model.

7.2.1 STATISTICAL TEST: PRE TREATMENT OUTPUT DROP

To verify the assumption that participation in the treatment is independent of idiosyncratic shocks, it was used the Ashenfelter test. This approach allows to analyze any outcome variations before the treatment begins, by comparing the outcome changes between the treatment and control groups. Specifically, it was calculated the difference in outcome over time for each country and then estimated the following linear model,

$$\Delta \mathrm{Y}_{its} = \alpha_i + \gamma_t + \beta \cdot \mathrm{treatment}_{is} + \epsilon_{its}$$

where ΔY_{its} is the variation of the outcome variable, Wages or GDP, α_i is the fixed effect for each country i, γ_t is the fixed temporal effect for the period t, β is the coefficient that measures the effect of the treatment on the variation of the outcome variable, $treatment_{is}$ is the variable that observes if the observation has received the treatment or not to the treatment variable and finally ϵ_{its} is the idiosyncratic error.
To check the assumption the coefficient β must not be statistically significant.

For the output variable Wages, the coefficient is not statistically significant for all three sectors, with a p-value of: 0.76 for the primary, 0.77 for the secondary and 0.77 for the tertiary.

For GDP, instead only the secondary is statistically insignificant (p = 0.125), while the primary and tertiary sectors (p = 0.001 and p = 0.003 respectively) are statistically significant, indicating significant pre-treatment differences between the treatment and control groups.

So it can be said that also the second assumption is satisfied for Wages for all three sectors, while for GDP it holds only for the secondary sector: the estimated effects in the primary and tertiary sectors should be interpreted with caution, as they may reflect pre-existing sectoral dynamics rather than the causal impact of the interest hikes.

7.3 ABSENCE OF SYSTEMATIC COMPOSITION CHANGES WITHIN EACH GROUP ASSUMPTION

This assumption concerns the composition of the groups being compared over time: to ensure that the observed results truly reflect the effect of the treatment or policy, it is important that the treatment and control groups do not change systematically in their characteristics over time. For example, if one of the groups changes significantly between the period before and after the intervention, the differences in outcomes could be attributed to these compositional changes rather than the effect of the treatment.
Since longitudinal data are used in this case, the issue of changes in group composition is less of a concern, as the same units are tracked over time, unless there is substantial data attrition. However, despite this consideration, an assumption check is still performed to ensure the reliability of the results.

7.3.1 COVARIANCE BALANCE TEST BETWEEN PRE AND POST

In this part of the analysis, the means of the key covariates are compared between the pre and post periods, separately for the treatment group and the control group. The goal is to see if these covariates (e.g. control variables) remain stable within each group, regardless of the treatment effect. If the means of the covariates do not differ significantly between the two periods, it can be concluded that there are no signs of systematic changes in the composition of the groups.
To verify this, statistical tests, such as the two-sample t-test, are used to analyze whether the observed differences in the covariates are statistically significant.

T-test results for Employment show that for all three sectors, the average difference between the pre- and post-treatment periods is very small in both groups, and the results are not statistically significant ($p > 0.05$). Therefore, we can conclude that no systematic changes in the composition of the Employment variable are observed.

T-test results for Inflation, on the other hand, show that for all three sectors, the average difference between the pre- and post-treatment periods is quite noticeable, with a clear increase, and the results are statistically significant ($p < 0.05$). Therefore, we can conclude that there are systematic changes in the composition of the Inflation variable, which increased significantly after the treatment. This could represent a violation of the assumption of no systematic changes in the composition.

7.3.2 REGRESSION ON COVARIATES TO ASSESS COMPOSITIONAL CHANGES

The objective remains the same, but done through a regression-based approach to obtain more consistent results. The use of regression allows us to account for multiple factors simultaneously, providing a more detailed and precise view compared to the covariate balance tests, and offers a quantitative estimate of the extent of these compositional changes.

The following model is estimated,

$$\mathrm{Y}_{is} = \beta_0 + \beta_1 \cdot \mathrm{post}_{ts} + \beta_2 \cdot \mathrm{treatment}_{is} + \beta_3 \cdot (\mathrm{post}_{ts} \times \mathrm{treatment}_{is}) + \epsilon \tag{5}$$

Here Y_{is} are the covariates, where i are Employment and Inflation. β_t are the coefficients that are estimated, *post* is the dummy variable that is equal to 0 for the period pre july 2022 and equal to 1 otherwise, *treatment* is the dummy variable that identifies with 1 the treatment group and with 0 the control group and $post * treatement$ which is the interaction variable.
If the interaction between the post period and the treatment group is significant, it indicates that the composition of the treatment group has changed differently compared to the control group during the analysis period.

Regarding the Employment variable, we can confirm the absence of systematic changes in all three sectors because the interaction between the post-intervention period and the treatment group is never significant ($p > 0.05$). Therefore, the assumption is satisfied.

For the Inflation variable, however, there are some differences: first, the interaction variable, which needs to be checked to verify the assumption, is not significant only in the first sector, meaning that only in this sector the assumption could be confirm, despite the fact that the variable still increases significantly in the post-intervention period. The Inflation variable violates the assumption for the remaining two sectors but it was still decided to include it in the analysis since inflation is a direct result of monetary policies. Therefore, it is essential to include it in order to measure the effect of the interest rate hike: if inflation changes systematically after the intervention, this could actually be a sign that the ECB's policy had a direct impact on the economy and the inclusion of this variable is not only justified but essential.

So in the end it can be said that also this last assumption is globally satisfied.

8 APPENDIX B

This Appendix provides comprehensive diagnostics that assures the robustness of the models implemented for each sector.

8.1 OUTLIERS

The focus is on identifying and handling outliers in the dataset in the outcome variables, to determine whether the model's conclusions are reliable and not overly influenced by extreme values in the data.
The outliers were identified using the z-score method which standardizes the data and identifies values that are more than three standard deviations away from the mean. A z-score was calculated for each observation of the outcome variables, and those with an absolute value greater than 3 were considered outliers: this outliers were then extracted and reviewed to understand which observations are likely to be extreme cases.

The z-score didn't identify any outlier in neither of the three sectors for the output variable Wages and for the variable GDP.

So it can be said that the model is robust to outliers.

8.2 HETEROGENEITY OF TREATMENTS

The goal is to examine the heterogeneity of the treatment effect based on the two control variables: the level of employment and the level of inflation. These additional controls allow us to verify whether the treatment effect varies significantly for groups with different characteristics in relation to these two variables and to strengthen the robustness of the model.
In both cases, the control variable in question was first divided into high and low levels, using the median. Subsequently, the following regression model was estimated to examine whether the treatment effect differs between the groups with high and low levels of the variable.

$$\begin{aligned}
\mathrm{Y}_{its} = {} & \beta_0 + \beta_1 \cdot \mathrm{post}_{ts} + \beta_2 \cdot \mathrm{treatment}_{is} + \beta_3 \cdot \mathrm{X}_{is} \\
& + \beta_4 \cdot (\mathrm{post}_{ts} \cdot \mathrm{treatment}_{is}) + \beta_5 \cdot (\mathrm{post}_{ts} \cdot \mathrm{X}_{its}) \\
& + \beta_6 \cdot (\mathrm{treatment}_{is} \cdot \mathrm{X}_{its}) + \beta_7 \cdot (\mathrm{post}_{ts} \cdot \mathrm{treatment}_{is} \cdot \mathrm{X}_{its}) \\
& + \beta_8 \cdot \mathrm{Z}_{its} + \gamma_c + \gamma_y + \gamma_q + \epsilon_{its}
\end{aligned}$$

where

- Y_{its}: is the outcome variable GDP and Wages.
- post_{ts}: is the variable indicator for the post treatment period.
- treatment_{is}: is the variable indicator for the treatment group.
- X_{its}: is the variable indicator for the high level of the control variable (employment or inflation).
- Z_{its}: is the other control variable, so if X_i is inflation then this variable will be Employment and viceversa.
- γ_c, γ_y, γ_q: fixed effects for Country, Year and Quarter.
- ϵ_{its}: is the error term.

8.2.1 HETEROGENEITY BY EMPLOYMENT LEVEL

The variation in the treatment effect on **Wages**, depending on the level of Employment, is examined through a three-way interaction term (`post` × `treatment` × `High_Employment`):

- In both the *primary* and *secondary* sectors, the coefficient of the three-way interaction is statistically significant, but with opposite signs, suggesting sector-specific heterogeneity. In the primary sector, the interaction is negative ($\beta_7 = -0.294$, $p = 0.038$), indicating that the treatment effect on wages is weaker in areas with high employment levels, while in the secondary sector, the interaction is positive ($\beta_7 = 0.191$, $p = 0.046$), suggesting that the treatment effect on wages is stronger in high-employment areas.
- In the *tertiary sector*, the three-way interaction is not statistically significant ($\beta_7 = -0.169$, $p = 0.350$), indicating that there is no evidence of heterogeneous treatment effects with respect to employment level. However, the two-way interaction `post` × `High_Employment` is negative and significant ($\beta = -0.217$, $p = 0.034$), suggesting that wages grew less in high-employment areas after the treatment, regardless of treatment status.

Similarly, the variation in the treatment effect on **GDP**:

- In the *primary* and *secondary* sector, the triple interaction is statistically significant: in the primary sector is negative ($\beta_7 = -0.197$, $p = 0.001$), suggesting that the positive treatment effect on GDP is notably attenuated in areas with higher employment levels. In contrast in the secondary it is positive ($\beta_7 = 0.136$, $p < 0.001$), so the overall impact of the treatment on GDP is stronger in regions characterized by high employment levels.
- In the *tertiary* sector, the three-way interaction is not statistically significant ($\beta_7 = -0.082$, $p = 0.174$), indicating no strong evidence that the treatment effect on GDP differs by employment level. However, the two-way interaction between `post` × `High_Employment` is significantly negative, which implies that GDP growth tends to be lower in high-employment areas irrespective of treatment.

8.2.2 HETEROGENEITY BY INFLATION LEVEL

The variation in the treatment effect on **Wages**, depending on the level of Inflation, is examined through a three-way interaction term (`post` × `treatment` × `High_Employment`):

- In both the *primary* and *tertiary* sectors, inflation significantly moderates the treatment effect on wages, with a negative and significant three-way interaction: primary ($\beta_7 = -0.402$, p = 0.020) and tertiary ($\beta_7 = -0.562$, p = 0.007). These results suggest that in high-inflation contexts, the treatment effect on wages is significantly reduced.
- In the *secondary* sector, the interaction is not significant ($\beta_7 = -0.041$, p = 0.700), indicating no substantial difference in treatment effects between high- and low-inflation areas.

Instead, the variation in the treatment effect on **GDP**:

- In the *primary* and *tertiary* sectors, the triple interaction is negative and statistically significant ($\beta_7 = -0.203$, $p = 0.014$; $\beta_7 = -0.311$, $p < 0.001$), indicating that the treatment effect on GDP is notably reduced in high-inflation contexts.
- In the *secondary* sector, the triple interaction is negative and marginally significant ($\beta_7 = -0.155$, $p = 0.062$), suggesting a potential weakening of the treatment effect under high inflation, although the evidence is less robust.

8.3 MULTICOLLINEARITY

Finally, the issue of multicollinearity in the estimated model was examined. Multicollinearity occurs when two or more independent variables are highly correlated with each other, which can negatively affect the stability and reliability of the coefficient estimates in the regression model. To address this, the Variance Inflation Factor (VIF) was calculated for each independent variable included in the model, so inflation, employment, post-treatment, and the interaction between the last two. The VIF measures how much the variance of a regression coefficient increases due to its correlation with other variables: high VIF values (typically above 5 or 10) indicate strong multicollinearity. This check is important to ensure that the estimates are robust and reliable and to identify any variables that might pose problems within the model.

For GDP as outcome variable, the VIF values for all variables and for all sectors are below the common threshold of 5 (Table 7, 8 and 9).

Variable	**VIF**
post	2.16
treatment	1.52
employment	1.32
inflation	1.27
post:treatment	2.21

Table 7: Primary Sector

Variable	**VIF**
post	2.40
treatment	1.40
employment	1.21
inflation	1.55
post:treatment	2.22

Table 8: Secondary Sector

Variable	**VIF**
post	2.16
treatment	1.21
employment	1.02
inflation	1.33
post:treatment	2.24

Table 9: Tertiary Sector

For the output variable Wages, there weren't indipendent variable with VIF higher then 5 for all three sectors, so there weren't any multicollinearity problems (Table 10, 11 and 12)

Variable	**VIF**
post	2.18
treatment	1.52
employment	1.32
inflation	1.23
post:treatment	2.20

Table 10: Primary Sector

Variable	**VIF**
post	2.39
treatment	1.40
employment	1.21
inflation	1.46
post:treatment	2.20

Table 11: Secondary Sector

Variable	**VIF**
post	2.19
treatment	1.21
employment	1.02
inflation	1.29
post:treatment	2.22

Table 12: Tertiary Sector

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