Evaluating the Impact of the New Triage Policy on Emergency Room Activity

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This study evaluates the impact of the new mandatory telephone pre-triage system on the number of emergency room visits. To assess this impact, publicly available emergency statistics from the Vila do Conde emergency room, one of the three hospitals involved in the trial, were used. Based on insights from domain experts, the emergency room in Barcelos served as a control group. The study focuses exclusively on the use of SARIMA models and transfer functions to develop a simple counterfactual as a quick means of identifying potential areas for further investigation. The findings suggest that, although the intervention led to a reduction in emergency occurrences during the period from January 2024 to September 2024, the impact was modest. The study concludes with several additional questions that could help refine the analysis and motivate further research, potentially using more advanced modeling techniques

1. Introduction

1.1 Motivation

The high pressure on emergency rooms has long been a significant concern for the Portuguese National Health System. This issue becomes particularly problematic during periods of increased demand, such as the winter season, when the pressure is exacerbated by the seasonal flu and other similar illnesses. In response to these challenges, public health authorities introduced a mandatory telephone pre-triage system, which was initially trialed in December 2023 at a limited number of locations. Alongside this, a new policy was implemented to refer patients to private hospitals. The mandatory pre-triage system is now promoted as a central component of the government's strategy to alleviate emergency room congestion.

This study is motivated by an initial analysis conducted by Professor Pedro Pita Barros, an economics professor at Nova SBE and a recognized expert in health economics. His analysis, published on December 18, 2024, examined emergency occurrences at the Unidade de Saúde de Vila do Conde (ULS Vila do Conde), one of the trial locations, and tracked the evolution of emergency room visits following the introduction of the mandatory pre-triage system in January 2024. In his study, the city of Barcelos was used as a comparison group to assess the potential impact of the intervention (see Barros and SBE 2024b).

Building on this initial work, the present study aims to explore whether SARIMA models, incorporating an external variable informed by domain expert knowledge, can offer a preliminary evaluation of the intervention's impact. Similar to Barros' study, ULS Barcelos will be used as a control group to generate a counterfactual, enabling the assessment of the potential effects of the pre-triage system.

While Barros' article identified some limitations in both the data and analysis, particularly regarding the use of total monthly emergency visits as a proxy for the intervention's impact, this study will not directly address these limitations. Instead, the focus here is on employing a different statistical approach to analyze the same data under similar assumptions. Additional assumptions and simplifications will be made throughout this study, and these will be clearly outlined as we progress.

1.2 Exploring data on emergencies for Vila do Conde and Barcelos

This study focuses exclusively on data from two institutions:

- **Hospital Santa Maria Maior, EPE**, which was renamed in 2024 to **Unidade Local de Saúde de Barcelos**.
- **Centro Hospitalar Póvoa de Varzim/Vila do Conde, EPE**, which was renamed in 2024 to **Unidade Local de Saúde de Póvoa de Varzim/Vila do Conde**.

The dataset includes information on various types of emergency incidents. However, this analysis focuses specifically on general emergencies. The data was retrieved from the public portal of the Portuguese National Health Service at https://transparencia.sns.gov.pt/explore/dataset/atendimentos-por-tipo-de-urgencia-hospitalar-link/information/?sort=tempo.

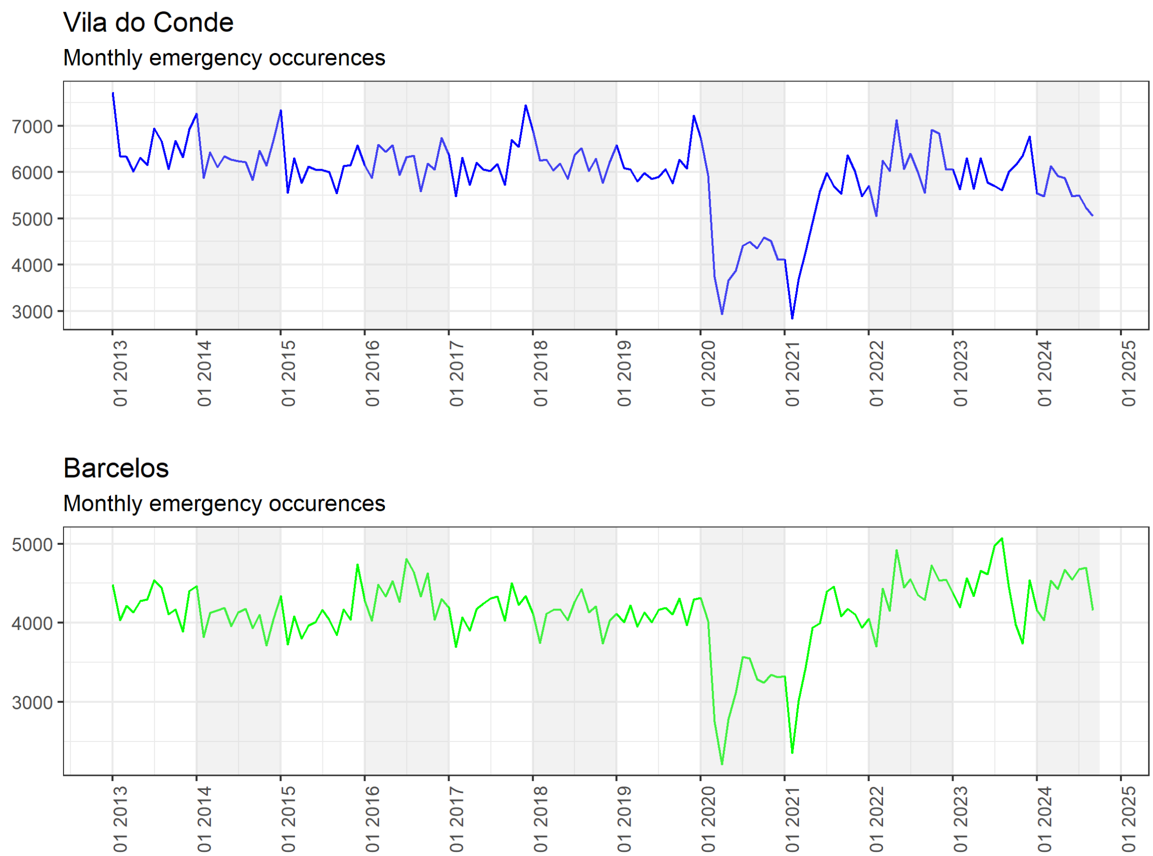

Figure 1: Monthly emergencies for both intervened and control series

There is a significant period of outlier behavior between January 2020 and April 2024, corresponding with the COVID-19 pandemic. This period caused substantial disruptions, which must be addressed before further modeling. The extended duration and magnitude of these anomalies require a strategy for outlier compensation.

Seasonality: The data exhibits signs of a **12-month seasonal pattern**, with local peaks typically occurring toward the end of each year.

Trends: Although no clear overarching trend is evident, there is a noticeable **continuous decrease in emergency occurrences** in Vila do Conde during the most recent months.

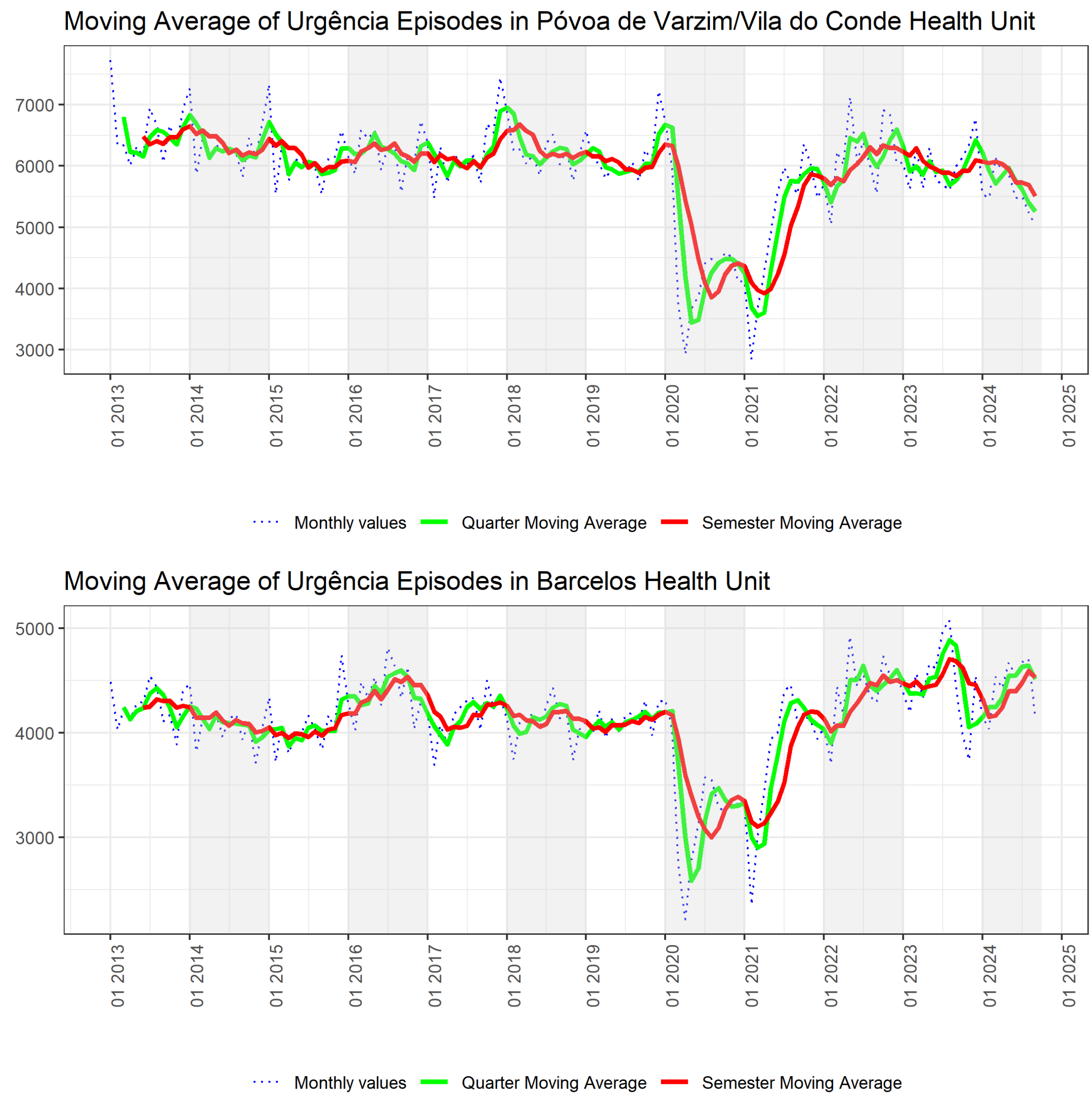

Figure 2: Monthly emergencies smoothed by Quarter and Semester moving average

An initial examination of the monthly emergency data for both locations revealed the following insights:

Smoothing both series using 3-month and 6-month moving averages highlights the following:

- The significant impact of the COVID-19 pandemic, which seems to have had lingering effects, as the series after that period show changes in trend and patterns.

- The pre-COVID series exhibited a very tenuous trend. Despite some periods, such as 2016 in Barcelos and 2018 in Vila do Conde, initial visual inspection reveals no clear significant change in the series mean. These periods appear to be point-in-time interventions or outliers. Analyzing each of these is beyond the scope of this study.
- The post-COVID period shows notable changes compared to the previous period, suggesting that the pandemic left lingering effects over time. In Vila do Conde, an upward trend in 2012 seems to have been followed by a downward trend starting in 2013 (the mandatory pre-triage intervention began in January 2024). A quarterly moving average below the semiannual average implies that this trend persists over time. In contrast, Barcelos has shown a continuous upward trend since the end of the pandemic. The sharp decline at the end of 2023 appears to be an outlier due to a shortage of practitioners, leading to the closure of several emergency services during that period. In 2024, Barcelos seems to demonstrate a sustainable upward trend.

A major takeaway from the visual inspection is that both time series are **non-stationary**. This conclusion is further supported by the **Kwiatkowski–Phillips–Schmidt–Shin (KPSS)** and **Augmented Dickey–Fuller (ADF)** tests. Since the goal is to study the impact of an intervention or policy change on the rate of increase or decrease in emergency visits, transforming the main series into a **logarithmic rate of change** allows us to achieve a similar goal while simplifying the modeling process. Let \$X\$ represent the random variable of monthly emergencies, and we will use the following variable for our analysis.

$$Z_n = ln(\frac{X_n}{X_{n-1}})$$

Figure 3: Monthly emergencies Log variations

Figure 4: Monthly emergencies Log variations and moving average

Fig show the transformed series with stationary despite the clear outlier moments during covid.

2. Assessing the impact of new pre-triage policy

2.1 Approach

Intervention analysis, introduced by Box and Tiao (1975), provides a framework for evaluating the effect of an intervention on a time series under study. The approach assumes that the intervention affects the process by altering the mean function or trend of the time series (Cryer and Chan 2009a , pp. 249).

In this context, addressing the mandatory pre-triage system as a new intervention is a valid approach. Given the nature of the intervention, it is necessary to model not only the short-term or immediate effects but also any spillover effects, as such changes are expected to generate lingering impacts over time with variable effects. A simple step or pulse function would not adequately capture the full scope of the intervention's impact. However, due to limited domain knowledge, it is not feasible to estimate all potential effects precisely.

Barros' article offers valuable insights by presenting Barcelos as a related series, with shared characteristics that make it a suitable control group for comparison (see Barros and SBE 2024b). It is important to note, however, that using another series to measure the intervention's impact comes with certain caveats:

- **Local interventions in Barcelos:** Emergency services in Barcelos were subject to local interventions, such as decisions made by hospitals, which could influence the analysis. It will be assumed that these local interventions did not significantly affect the outcome of the study.
- **Outliers in both series:** As previously noted, both series contain outliers, which may be caused by events such as strikes or doctor shortages. For the purposes of this study, these periods will not be excluded or treated as outliers (e.g., using a pulse dummy variable and modeling it as an external variable). Therefore, it is assumed that, while these outliers exist, they will not substantially impact the modeling process or the final results. This is a simplification, and addressing these outliers would require additional analysis outside the scope of the current study.

2.1.1 Covid-19

Both the original and transformed (log returns) series show a significant disruption during the COVID-19 pandemic period. The available metadata is insufficient to determine whether emergencies during this period were recorded in a separate dataset or if these two institutions were closed or operating under limited capacity. However, unlike other periods of identified outliers in both series, the magnitude and duration of the COVID-19 impact are substantial enough to significantly affect any model generated from this time series.

An intervention or outlier approach using external variables could be useful in this case(Cryer and Chan 2009a , pp. 257). However, the primary objective here is to use historical data to infer the existence of a significant impact from a recent policy change. Given these circumstances, the focus is on identifying strong trends and seasonality, rather than analyzing specific past effects, which, while influential, are not replicable despite any spillover effects they may have had. Therefore, the COVID-19 impact will be "removed" from the series by "forecasting" the data between January 2020 and March 2021.[1]

2.2 Methodology used to assess the intervention

Given the proposed goal and the assumptions outlined in the previous analysis, the impact of the mandatory telephone pre-triage (hereafter referred to as **SNS24 triage**) at ULS Vila do Conde will be evaluated as follows:

1. A counterfactual series will be forecasted using historical data from Vila do Conde, with **Barcelos** serving as an external variable and acting as a control group.
2. Data from 2013 to 2020 will be used to replace the COVID-19 period from January 2020 to March 2021.
3. The newly generated series for the period 2013-2023 will be used to fit a model, which will then generate the counterfactual. Given the objectives of this study, no smoothing will be applied between the actual series from 2013 to 2020 and the COVID-19 replacement period.

3. Counterfactual and measuring intervention

3.1. Covid-19 outlier period

Figures 4 and 5 isolate the series between February 2013 and December 2019 (the original series includes January 2013, but the first observation was removed due to the transformation to avoid 0 or infinite variations). As discussed earlier, both series show signs of outliers, particularly around the start of 2014 and 2015.

The **Autocorrelation Function (ACF)** and **Partial Autocorrelation Function (PACF)** show substantial correlation at 12 and 24 lags in both series, suggesting a yearly pattern, consistent with monthly data. This aligns with expectations given the nature of the dataset.

[1] It's important to notice that forecasting in order to reconstruct a period of a time series does introduce a substantial level of bias and noise to the analysis. Although it's assumed that this effect does not impact the outcome and conclusions, further analysis is required to validate this assumption in future works.

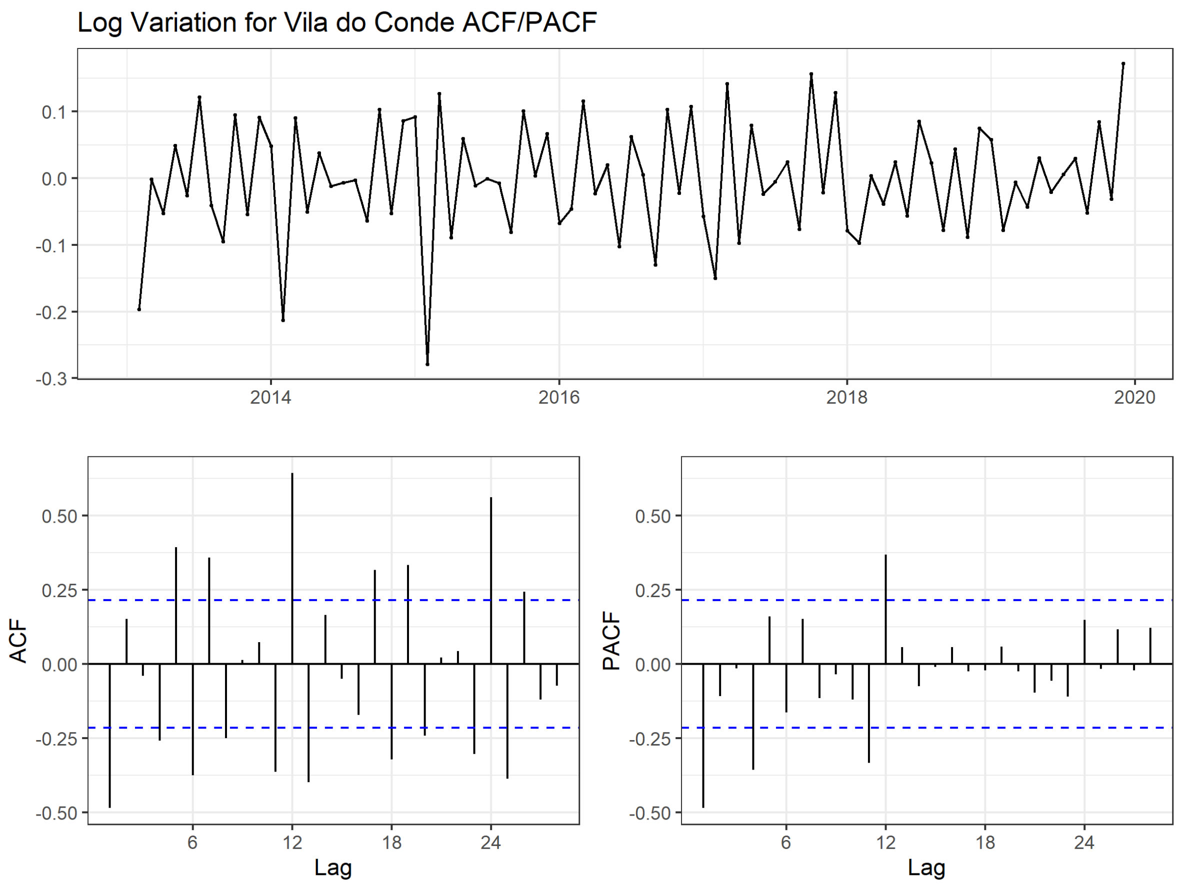

Figure 5: ACF and PACF for Vila do Conde log variation

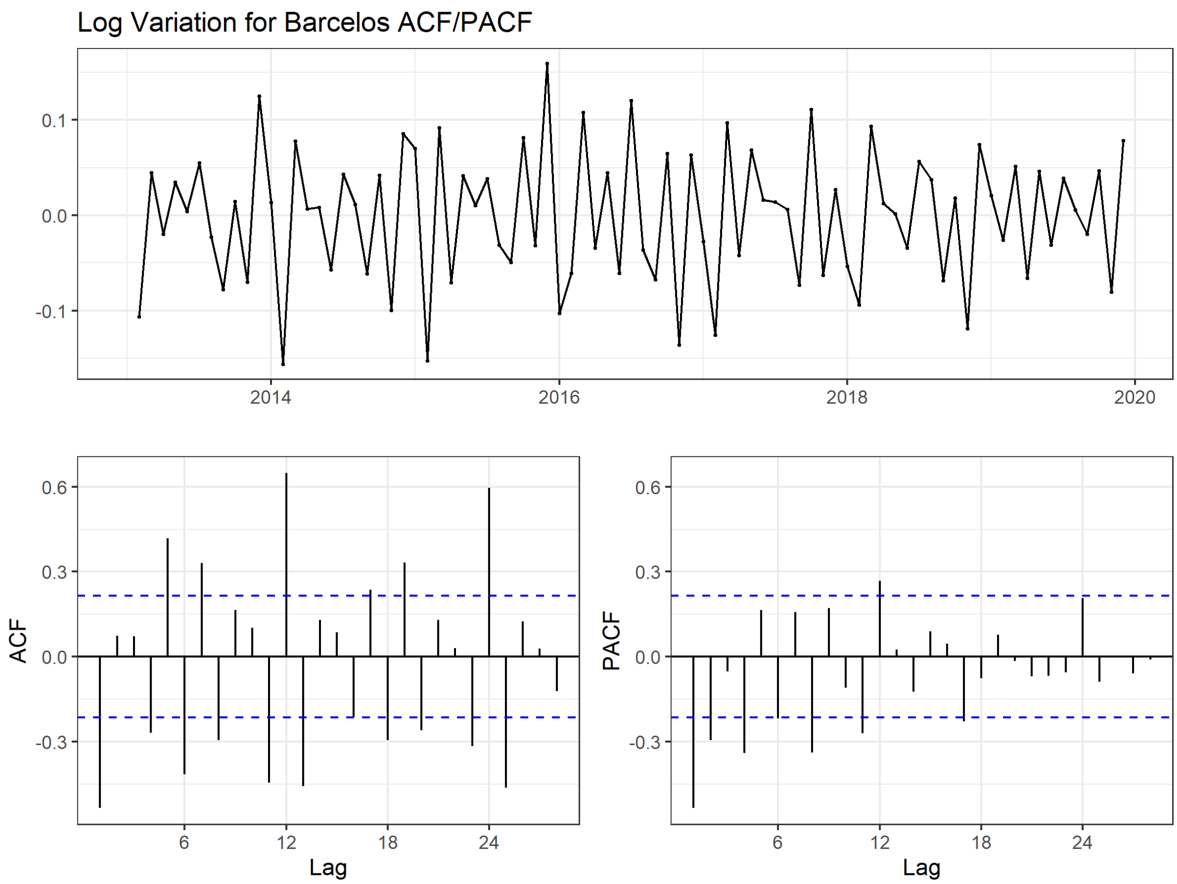

Figure 6: ACF and PACF for Barcelos log variation

Significant lags also exist at the 6 and 18 lags suggesting multi sesonality. Intuition suggests that a 6 month cycle could exist given the number of emergencies due to seasonal illnesses like flu which typical are at its high during winter.

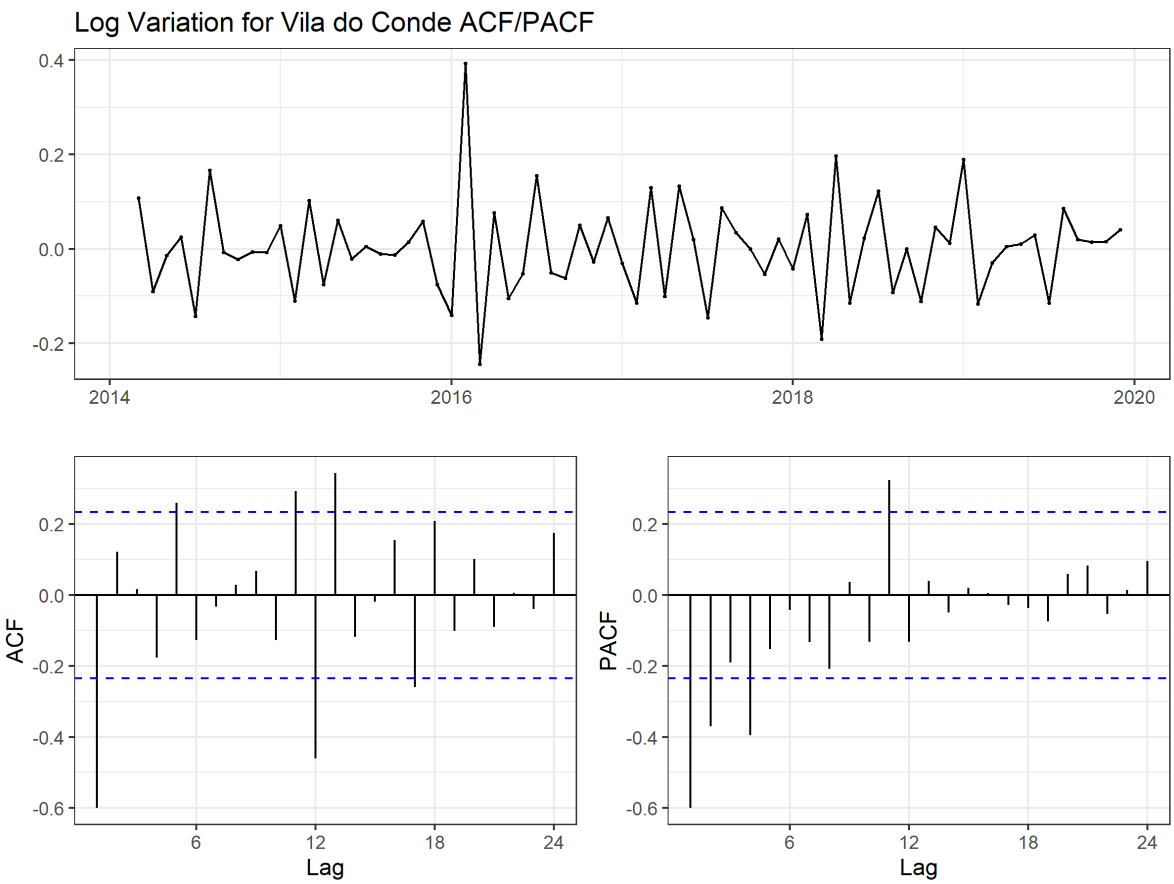

Figure 7: ACF and PACF for Vila do Conde log variation for (1-B)12

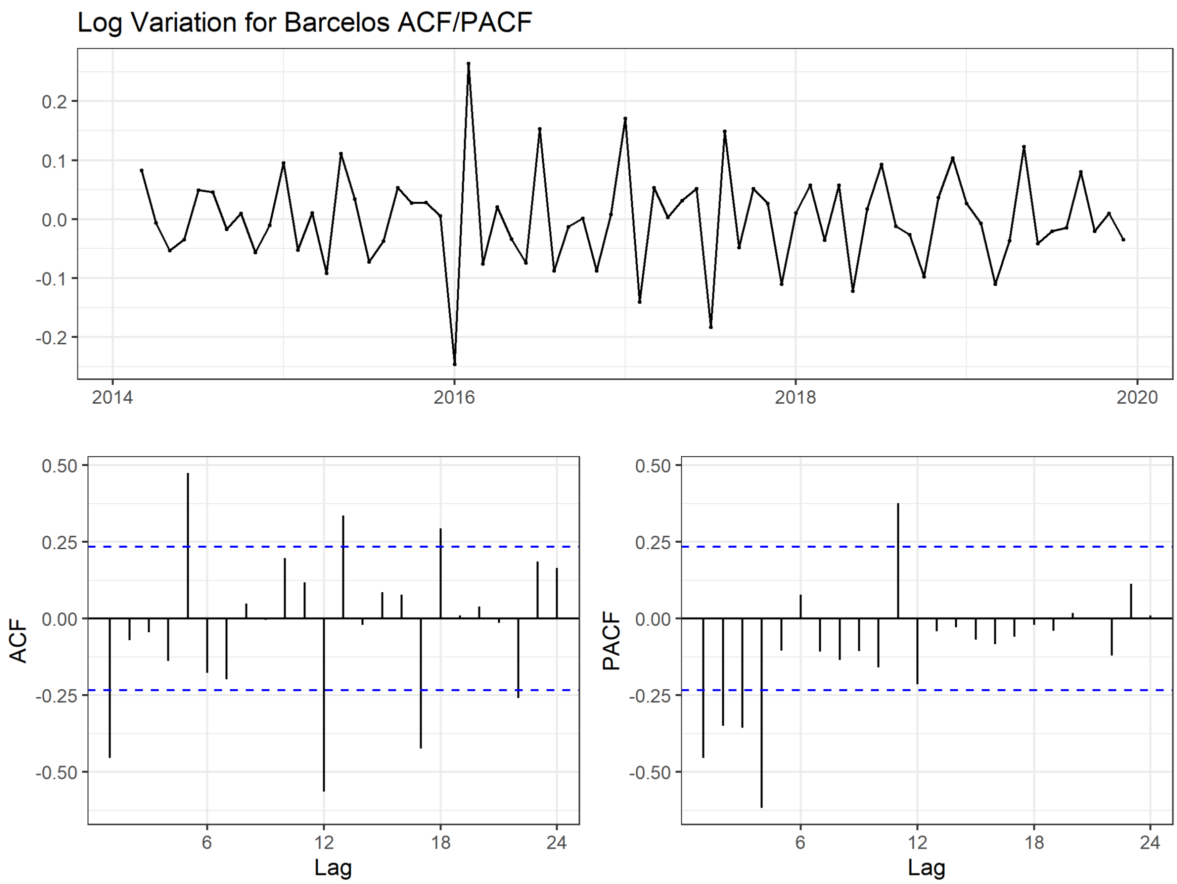

Figure 8: ACF and PACF for Barcelos log variation for (1-B)12

Analyzing both ACF/PACF and residuals a SARIMA(1,0,1) x (0,1,1)12 was used to model the pre-covid moment for Vila do Conde and a SARIMA(4,0,1) x (1,1,1)12 for Barcelos. Below the model statistics support this models as good approximations for the reality under study. [2]

[2]Further detail about pre-covid modeling can be found on appendix B.

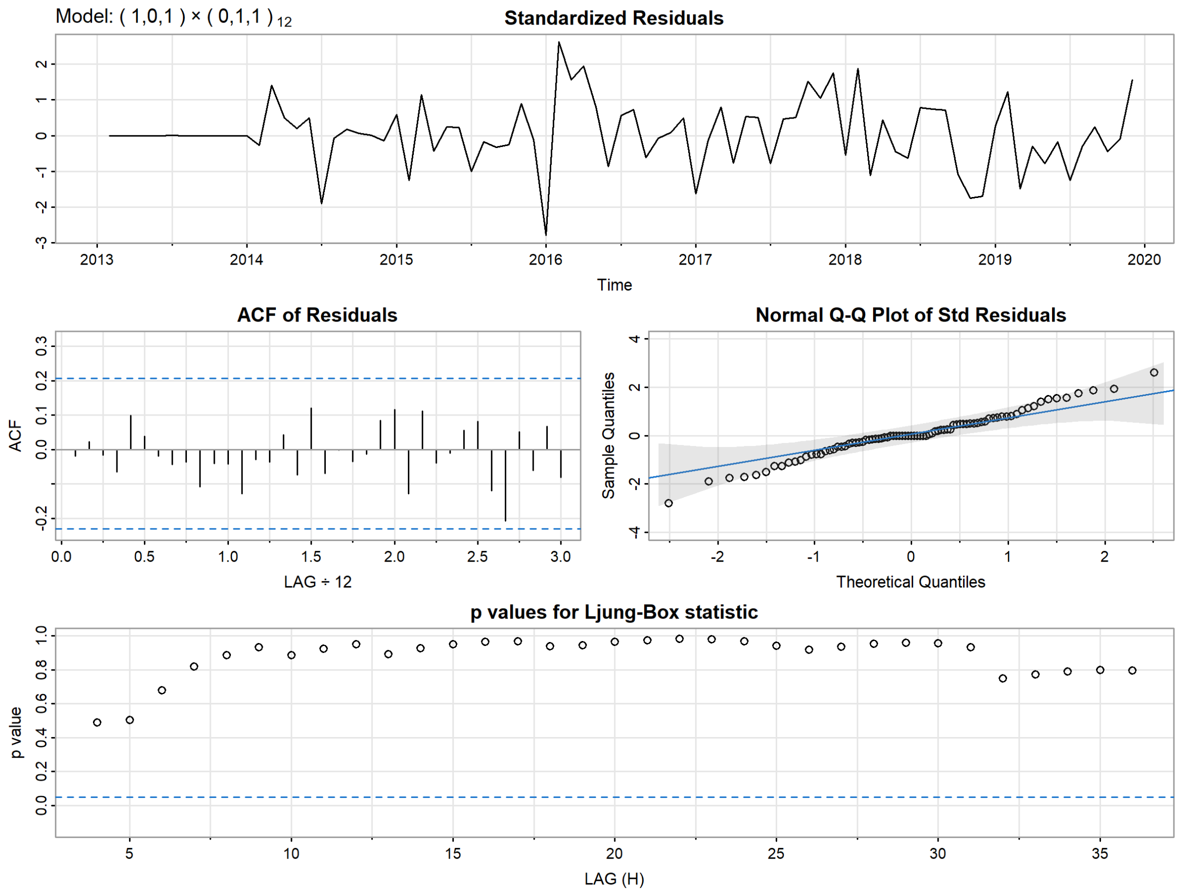

Figure 9: Vila do Conde Pre-covid model fit statistics

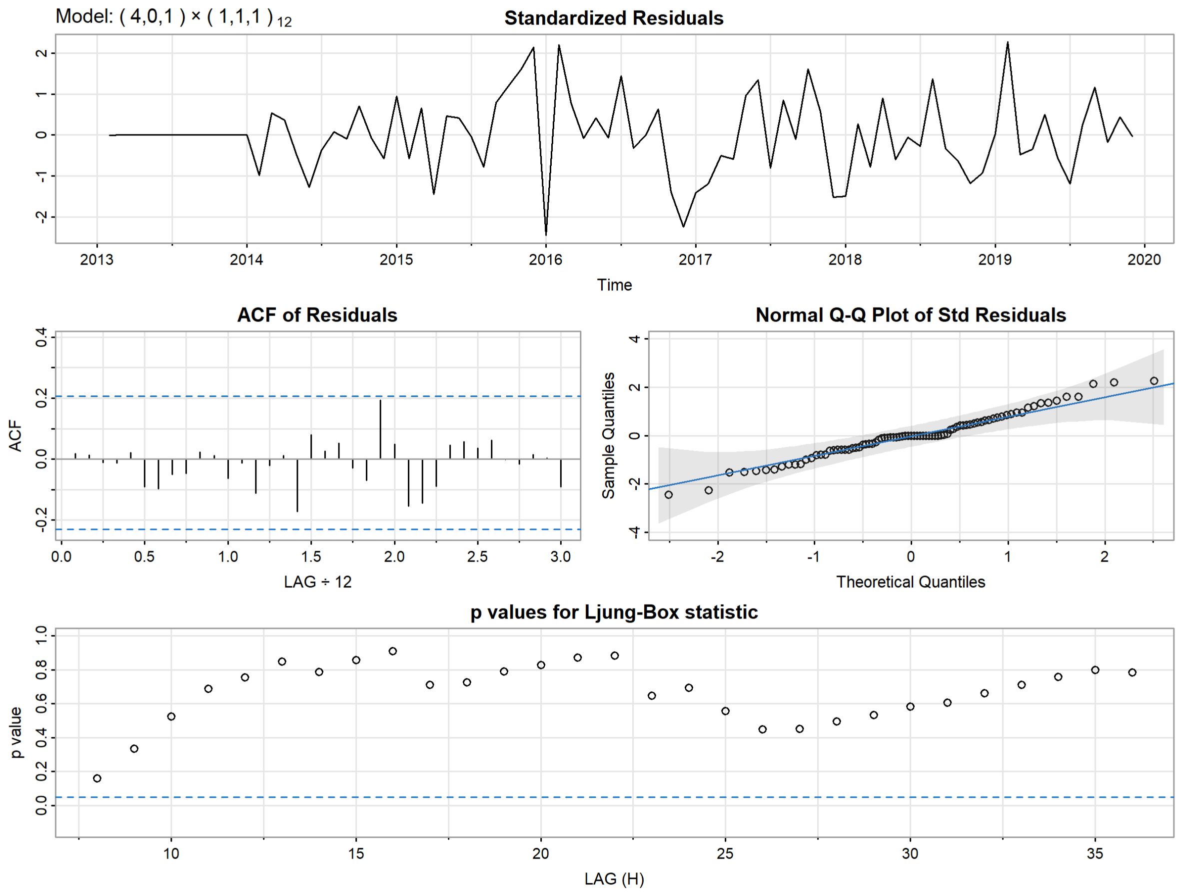

Figure 10: Barcelos Pre-covid model fit statistics

Using this model its now possible to replace the covid effect based on previous periods:

Figure 11: Series without Covid effect for both Barcelos and Vila do Conde

3.2. Fitting a Counterfactual

After correcting the series from 2013 to September 2024, it is necessary to verify whether the initial hypothesis, supported by domain knowledge, that **Barcelos** reflects a similar reality and can thus serve as a valid control series, holds true. Cross-correlation between both series shows a strong correlation at lag 0, indicating a strong instantaneous effect. This confirms that Barcelos can be considered a suitable candidate for the control group.

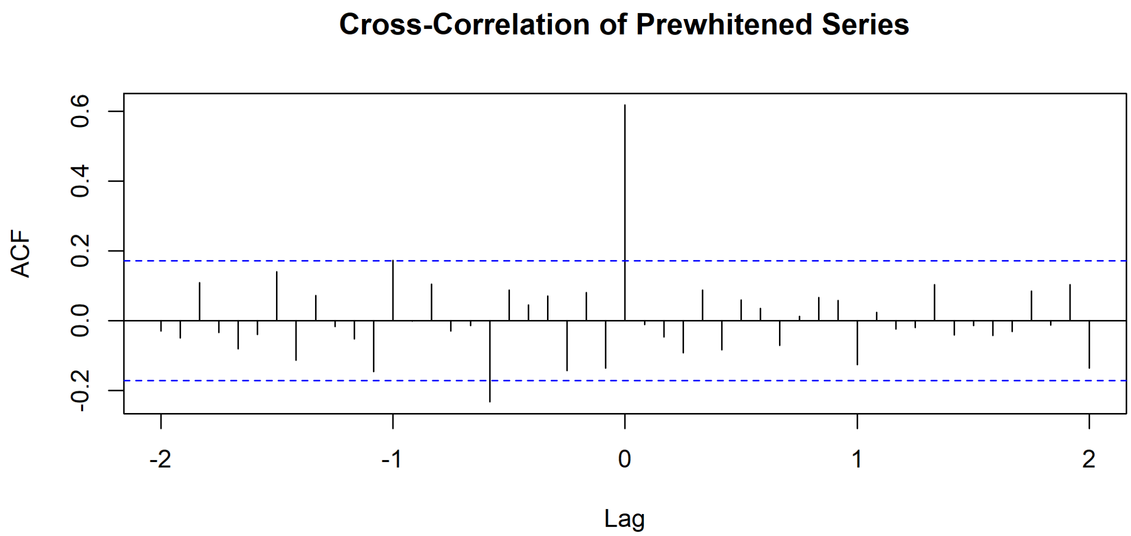

Figure 12: CCF between Barcelos and Vila do Conde

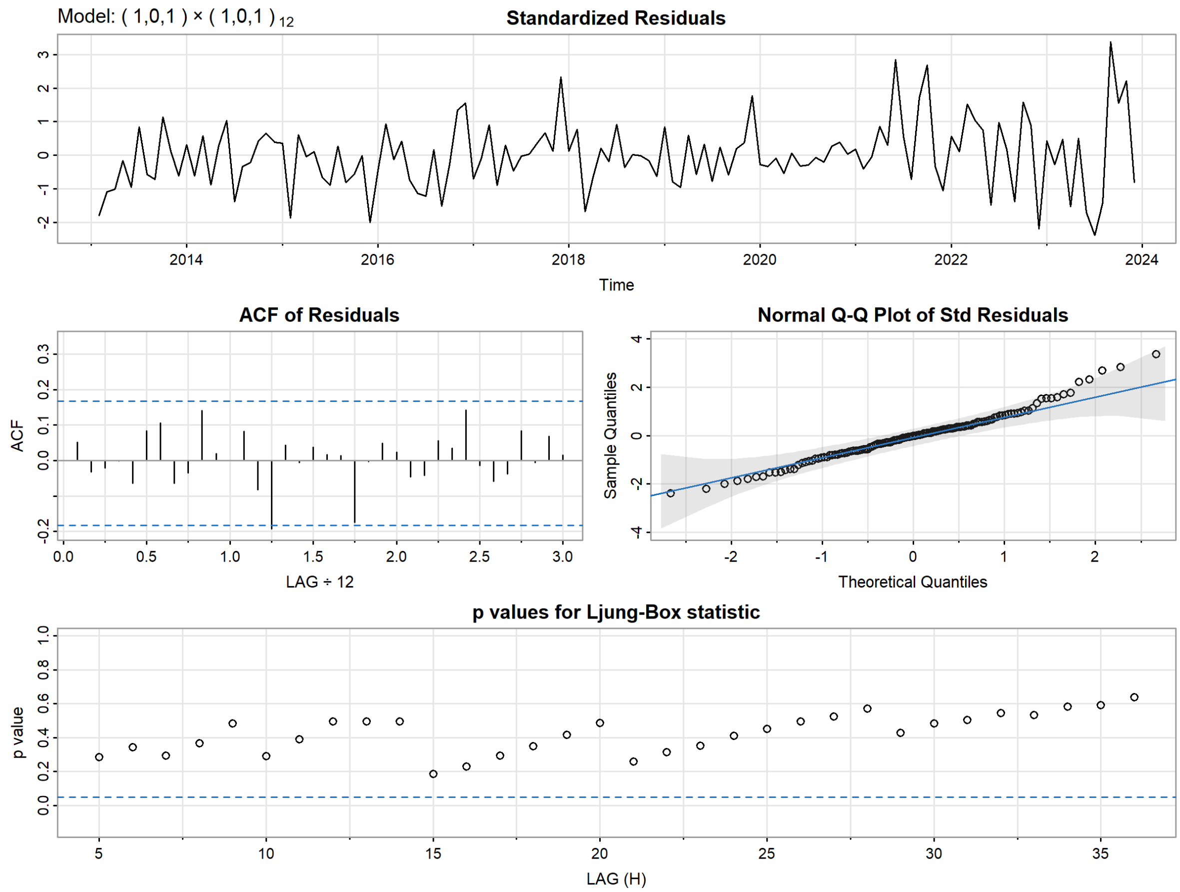

Figure 13: Counter factual model fit

Fitting a **SARIMA (1,0,1) x (1,0,1)** model with a 12-month seasonality and using **ULS Barcelos** as an exogenous variable produces a "good enough" model for the purposes of this analysis. The residuals show low correlation, suggesting that the model is adequately fitting the data. This model can then generate a "theoretical" series for the period between January 2024 and September 2024, the only available period during the intervention.

Visual inspection of **Figure 14** shows that both the sample data and the counterfactual closely follow one another. A **Welch two-sample t-test** confirms what can intuitively be inferred from the plot: both series are likely derived from the same distribution, as the null hypothesis (H0: difference in means = 0) cannot be rejected.

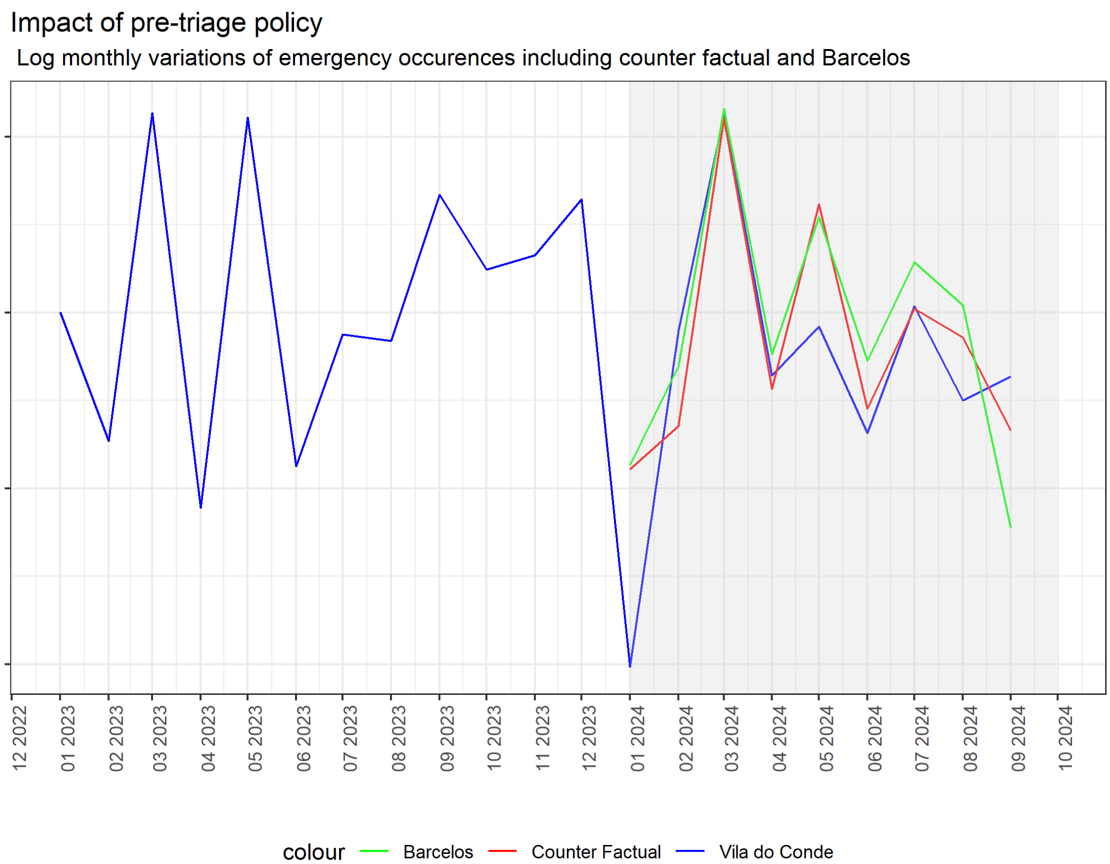

Figure 14: Comparing impact

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    Welch Two Sample t-test

data:  counter_factual.tibble$value and real.tibble$emergencias_mensais
t = 0.42968, df = 15.313, p-value = 0.6734
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.05959164  0.08975142
sample estimates:
  mean of x   mean of y 
-0.01763109 -0.03271098 
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4. Conclusion and future work

The counterfactual analysis of the implementation of the new health policy requiring a telephone pre-triage before visiting the emergency room shows that, based on one of the test locations, there was no immediate impact from this new intervention. In other words, the number of emergencies observed during the trial period would likely have occurred even if the intervention had not been implemented.

Despite these results, it is important not to hastily conclude the ineffectiveness of such policies. As highlighted by Barros and SBE (2024b) in the article that motivated this study, there are additional considerations and questions that should be addressed before drawing any conclusions, such as:

- Is the number of emergencies the best metric to measure the impact of such an intervention?
- Do other locations that participated in the trial period show similar results?
- In the event of a reduction in emergencies, where were the patients redirected?
- Does the data reflect a like-for-like comparison, ensuring a comparable situation between different periods (e.g., same number of doctors and nurses)?
- While this analysis focuses on the mean (the first moment), shouldn't the scope of such a policy also consider the predictability of random events (the second moment)?

The list of considerations goes on. At best, this study, with its simplified approach, highlights the complexities and nuances of data and impact analysis in the context of decision-making. It serves as a reminder that first impressions can be misleading.

References

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