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Unveiling the Impact of Anti-Mafia Judge Assassinations: A Quasi-Experimental Analysis of the Causal Relationship between Mafia Presence and Public Spending

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Abstract

This study investigates the causal relationship between the presence of the Mafia and public spending in Italy. Previous research suggests that the Mafia may exert its influence on public spending through political pressure or resource diversion, but the specific causal impact remains largely unexplored. To address this, the study utilises the Difference-in-Differences methodology and employs a Synthetic Control Method to assess the effect of Mafia presence on public spending. The primary dataset includes public spending data from 1987 to 1999, complemented by additional control variables. The analysis focuses on the assassinations of anti-Mafia judges Giovanni Falcone and Paolo Borsellino in 1992 as a significant event for estimation. The findings suggest that although Mafia presence may have some impact on certain aspects of public life, it does not seem to be the main factor driving public spending. Hence, the previously established correlation in existing literature between anti-Mafia legislation and its impact on public expenditure is likely to be associated with underlying factors that extend beyond the mere reduction of Mafia presence.

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1 Introduction

The presence of organised crime in Italy has been a long-lasting issue, with the Mafia being one of the most notorious criminal organisations in the country. A previous study conducted by Acconcia et al. (2014) demonstrated that efforts to combat the Mafia, such as the assignment of external commissioner administration by the central government to certain municipalities, temporarily reduced the public spending multiplier. This intriguing finding raises the question: What is the relation between the Mafia presence and public spending? In this research, we want to investigate the causal effect of Mafia presence on public spending and see whether the reduction of Mafia presence actually dampens public spending.

Understanding the impact of the Mafia on public spending is of great importance for policymakers in Italy. It is essential to determine whether the presence of the Mafia affects public spending, as this can have significant implications for the country's overall economic growth. Moreover, the insights gained from this study can provide valuable information to shape policies that effectively combat organised crime and foster a transparent governance framework.

In light of the above, this study aims to investigate the causal relationship between Mafia presence and public spending in Italy. Specifically, we seek to determine whether the presence of the Mafia affects public spending using the Difference-in-Differences (DiD) (Lechner et al., 2011) methodology and a Synthetic Control Method (SCM) (Abadie et al., 2015). In our DiD estimation, we specifically focus on the assassinations of anti-Mafia judges Giovanni Falcone and Paolo Borsellino in 1992 as the event of interest. These events had significant national and international attention and were a turning point in Italy's fight against the Mafia (Calamunci et al., 2023; Paoli, 2007; Schneider, 2018).

We utilise the dataset from Acconcia et al. (2014) as our primary data source, which encompasses data on the extent of public spending across Italian municipalities from 1987 to 1999. The dataset also incorporates additional variables for control purposes, such as the unemployment rate, the number of council dismissals, and lagged values of public spending.

Our analysis provides strong evidence that the assassinations of the anti-Mafia judges had no immediate impact on public spending. The consistent findings from the DiD estimation and Synthetic Control estimation enhance the reliability of our results. Notably, the inclusion of lagged covariates and the expansion of our regressors did not alter these conclusions, further strengthening their validity.

Our research builds upon previous studies, including the work by Acconcia et al. (2014), which indicated that anti-Mafia measures, specifically compulsory council dismissals, were associated with temporary decreased public spending. Our findings challenge the existence of a causal relationship between Mafia presence and public expenditure. It appears that the observed effect on public spending may have been influenced by alternative factors or pathways, rather than being directly caused by changes in Mafia presence.

The paper is structured as follows: Section 2 delves into the existing literature and examines prior findings, enabling us to gain insights and formulate speculative hypotheses. In Section 3, we provide an explanation of the data source used to address our research question. This is followed by Section 4, where we describe the methodology employed to answer the research question. The results obtained from this methodology are presented in Section 5. Additionally, we offer a comprehensive explanation of how the key findings from the study conducted by Acconcia et al. (2014) were replicated in our research and assess the consistency of these findings. Finally, in Section 6, we discuss the conclusion, highlight the limitations encountered, and outline potential paths for future research.

2 Theoretical and Historical Background

2.1 Mafia Presence and Public Spending

The study of the causal relationship between the presence of the Mafia and public spending in Italy holds importance for several reasons. Italy has a long-lasting Mafia issue which is more prevalent in certain regions. Understanding how the Mafia's influence affects public spending can provide insight into the economic consequences of organised crime. This allows policymakers to identify potential economic distortions caused by the Mafia's involvement in public expenditure. Because Mafia presence is more pronounced in certain regions, investigating the impact of the Mafia can also shed light on regional disparities in economic development. Policymakers can devise targeted strategies to address these disparities and promote more equitable regional development.

Mafia presence can affect public spending through various channels. We put forth two theories, namely the Public Choice theory (Shaw, 2002) and the Rent-seeking theory (Tollison, 2004), to support our hypothesis regarding the impact of Mafia presence on public spending.

The Public Choice theory suggests that the presence of criminal organisations, such as the Mafia, may distort public spending decisions and resource allocations. The Public Choice theory is an economic and political theory that applies the principles of microeconomics to analyse decision-making processes in the public sector (Shaw, 2002). It explores how individuals, including politicians, make choices in the context of collective decision-making and public policy. The Public Choice theory operates on the assumption that individuals are rational and motivated by self-interest, with their primary objective being the maximisation of personal utility. Following this theory, Boetti et al. (2012) highlight how incumbent politicians' opportunistic behaviour influences spending performance and efficiency. This susceptibility to personal gain creates opportunities for corruption and the infiltration of public institutions, usually linked to the Mafia. According to Tanzi and Davoodi (1998), political corruption has a significant impact on the decision-making process related to public investments. Their research demonstrates that higher levels of corruption are associated with several adverse outcomes. While corruption may lead to higher levels of public investment, it is accompanied by lower government revenues, reduced spending on maintenance, diminished quality of public infrastructure, and lower overall productivity. These consequences contribute to hindered economic growth and development. Berrittella (2018) further emphasises that organised crime plays a significant role in areas where government effectiveness is limited, leading to an impact on the allocation of public spending for both local public and private services.

The second channel of influence utilises the Rent-seeking theory, which was initially introduced by Tullock (1967). The Rent-seeking theory is one of the first theories that provide an economic framework to model corruption in the public sector (Lambsdorff, 2002). There are two primary mechanisms at play. The first mechanism involves Contestable rent, which incentivises rent-seeking activities such as lobbying and corruption, aimed at gaining control over the rent. These activities result in the inefficient allocation of resources and a loss for society (Aidt, 2016; Tollison, 2012; Tullock, 1967). The second mechanism revolves around Rent-seeking costs, which are often not directly observable but can be inferred from the value of the contestable rent (Aidt, 2016; Tullock, 1967). It is important to distinguish the Rent-seeking theory from profit-seeking or entrepreneurship. Buchanan et al. (1980) emphasised that profit-seeking is productive, driving the creation of new products and efficient allocation of resources to higher-valued uses. In contrast, Rent-seeking is unproductive, wasting valuable resources and depreciating their value (Buchanan et al., 1980; Tullock, 1967). Additionally, corruption is often seen as a costless transfer of income from one party to another. However, Aidt (2016) argues that corruption has a broader social impact, leading to policy distortions and unfair allocations of public resources. He highlights underlying social problems associated with corruption and its negative implications for society. Furthermore, Mafia influence poses significant challenges to the rule of law. Corruption, intimidation, extortion and infiltration in public institutions can weaken governance structures and demolish public trust (Corbacho et al., 2015).

While the Public Choice theory emphasises the potential distortion of spending decisions due to the influence of criminal organisations, the Rent-seeking theory focuses on the unproductive use of resources and the social costs associated with rent-seeking activities.

2.2 Assassinations of the Anti-Mafia Judges

In 1982, the assassinations of Member of Parliament Pio La Torre and General Carlo Alberto Dalla Chiesa played a pivotal role in shaping anti-Mafia legislation (Calderoni et al., 2015). These tragic events led to the establishment of the Rognoni-La Torre Law, which aimed to strengthen the legal framework and empower law enforcement agencies in combating organised crime groups (Ayala and Fitzjohn, 2013; Smith, 2019). Similarly, following the murder of Giovanni Falcone, a new legislative decree known as the Falcone Act was enacted. This decree specifically addressed the conduct of trials and the actions of the police in the ongoing fight against the Mafia. Following the tragic death of Giovanni Falcone, an unprecedented number of demonstrators assembled and marched to honour his memory, precisely 30 days subsequent to the assassination (La Spina, 2004). Furthermore, in August 1992, after the assassination of Borsellino, Act No. 356 was implemented, granting the judiciary police increased responsibilities in areas such as wiretappings, searches, and interrogations (Paoli, 2007). These legislative measures represented significant steps taken to bolster the authorities' capabilities in tackling Mafia-related activities.

During the mid-1990s, the European Commission initiated the Falcone program, aiming to enhance communication and collaboration among European practitioners in addressing organised crime issues (La Spina, 2004). This program exemplifies how the deaths of the two anti-Mafia judges brought about lasting changes. La Spina (2004) also explains that following the murders of Giovanni Falcone and Paolo Borsellino, the Ministry of Justice and Interior took decisive action by establishing an Ad Hoc Working Group on International Organised Crime on September 18, 1992. The primary objective of this group was to explore ways to intensify the cooperative efforts of EU Council members in combating organised crime. These developments indicate a notable shift in focus and a strong determination to address the challenges presented by organised criminal activities.

Taking all these factors into account, it can be inferred that the assassinations of anti-Mafia judges Giovanni Falcone and Paolo Borsellino in 1992 exerted a substantial impact on the presence and influence of the Mafia in the municipalities affected by these tragic events. As a result, these assassinations are suitable as pivotal events within a DiD design to estimate the causal impact of Mafia presence on public spending.

2.3 Hypothesis

After the assassinations of the anti-Mafia judges in 1992, we expect that there would be an increase in public investment. This assumption is based on the belief that the government would allocate more funds towards enhancing public infrastructure in the regions affected by the Mafia, with the aim of diminishing its presence. The improvement of public infrastructure plays a crucial role in addressing crime. As demonstrated in the research conducted by Montolio (2018), investing in infrastructure not only leads to a temporary decrease in local unemployment rates but also significantly reduces crime rates.

Calamunci et al. (2023); Paoli (2007); Schneider (2018) indicate that Italy witnessed a significant surge in anti-Mafia movements following 1992. The unification of municipalities and their alignment towards shared objectives has proven to be effective in reducing crime rates, as explained by Alberti et al. (2023). This unity among municipalities could potentially have resulted in increased investment exerted by these regions to combat the Mafia. Additionally, the enactment of laws after the 1992 assassinations (La Spina, 2004; Paoli, 2007) facilitated municipalities and law enforcement agencies to combat the Mafia. Considering the nationwide determination to combat organised crime, there are grounds to believe that the government allocated funds to tackle the Mafia issue.

However, it is important to note that the rate at which public investment increased due to the assassinations of Giovanni Falcone and Paolo Borsellino may not be as substantial as expected. In a study that examined data from three distinct Italian regions across a period spanning from 1998 to 2013, Galletta (2017) made an interesting discovery. They found that the implementation of anti-Mafia measures, particularly those involving the dismissal of local councils, resulted in a decrease in public investment in nearby municipalities. The article attributes this reduction in investment to the spillover effect of law enforcement, effectively suppressing criminal activities in those neighbouring areas. Consequently, this finding suggests that a substantial increase in public spending may not be necessary due to the effectiveness of these spillover effects. Moreover, it is worth noting that due to the autoregressive nature of policy implementation (Calamunci et al., 2023), the direct impact of the deaths of Giovanni Falcone and Paolo Borsellino may not be immediately measurable.

3 Data

The data employed in this research is obtained from the dataset used by Acconcia et al. (2014), which was originally collected from multiple sources, including the Istituto Nazionale di Statistica (ISTAT, 2014), Istituto Guglielmo Tagliacarne (IGT, 2014), the Department of Internal and Territorial Affairs (DAIT, 2014), and the Italian Anti-Mafia Commission (Commissione Parlamentare Antimafia, 2014). It is important to note that the authors of the study, Acconcia et al. (2014), defined the variables and also performed the necessary data-cleaning procedures. To ensure the robustness of our research findings, we directly utilised the data from their cleaned dataset. This approach allowed us to validate their results and strengthen the reliability of our study.

The dataset we examined comprises data on public investment spending in each Italian province from 1987 to 1999. Within each province, multiple municipalities were documented, resulting in over 950 annual observations across 95 provinces. To estimate the public spending multiplier, we use the year-on-year percentage change of real (1995 price) per-capita public investment in infrastructure. Specifically, this value is used as the dependent variable in our DiD and Synthetic Control estimations.

One significant advantage of this dataset is that during the observation period, the central government had control over the flow of resources and the implementation of projects. This meant that the central government had the power to choose which projects were implemented and who would carry them out. However, local governments had limited power to set tax rates. This lack of power meant that any public resources channelled by the central government into local projects were not matched by changes in the tax burden of the residents. Therefore, we did not face any of the potential issues arising from the omission of tax changes (Acconcia et al., 2014).

Table 1 presents the summary statistics for key regions in Italy, providing an overview of important data points. The provided data displays the average values of observations before and after the tragic event involving the assassinations of the anti-Mafia judges Giovanni Falcone and Paolo Borsellino. The G variable is our dependent variable representing the year-on-year percentage change in public spending. The $Population$ variable is the total population of a region. $U2$ represents the change in the logarithm of per-capita hours of wage supplement, while the variable CD, which we refer to as "Council Dismissals", denotes the number of municipalities subjected to external commissioner administration by the central government due to evidence of ties with the Mafia. The complete summary statistic table can be found in Appendix B.

A treatment group is essential for conducting the necessary estimations in this study. The selected treatment group comprises observations from Sicilia, Calabria, Campania and Puglia. These regions are recognised for their significant Mafia presence and are even home to Mafia families (Acconcia et al., 2014; Draghi, 2011). Besides the DiD methods, we also employ the SCM. This requires us to also find potential Synthetic Control units that are similar to the aforementioned treatment group in pre-event characteristics. The potential control units are Basilicata, Friuli Venezia Giulia and Marche. Further reasoning for choosing these regions can be found in Section 4.2.

From Table 1, it can be observed that the mean for G in the pre-event period is very negative,

Table 1: Summary statistics of key regions

	G		Population		U2		CD	
	Post	Pre	Post	Pre	Post	Pre	Post	Pre
Sicilia	-0.174	-0.607	563837.7	551853.9	-0.195	-0.002	0.033	0.004
Calabria	0.010	-0.403	690277.8	693020.1	-0.024	0.009	0.009	0.029
Campania	-0.092	-0.659	1151041	1121259	0.003	-0.006	0.058	0.013
Puglia	-0.033	-0.148	815593.9	802345.4	-0.017	0.001	0.010	0.003
Basilicata	0.366	-0.672	304633.6	305386.7	-0.015	-0.005	0.003	0
Friuli Venezia Giulia	-0.070	-0.386	297137.6	300123.4	-0.002	0.016	0	0
Marche	-0.063	-0.267	361604.5	355776	-0.010	-0.006	0	0

Notes: G is the year-on-year percentage change of real per capita public investment in infrastructure. $U2$ represent the change in the log of per-capita hours of wage supplement provided by the unemployment insurance. And finally, *Council_Dismissal* (CD) represents the number of municipalities placed under external commissioner administration by the central government, indicating evidence of Mafia ties. The mean is given for data before and after 1992, indicated by post and pre-headers. In order to clarify the absence of reported council dismissals, certain values in the last column of the table are presented as 0. This was intentionally done to indicate that no council dismissals were reported, rather than suggesting a minute positive value.

indicating a significant decrease in real per-capita public investment in infrastructure compared to the lagged real per-capita value added. This suggests a decline in infrastructure investment before the event occurred. In the post-event period, the mean value for G is still negative but closer to zero. This implies that while there is still a negative change in real per-capita public investment, the decline has slowed down. *Population* shows a slight increase for Sicilia, Campania, Marche and Puglia but is generally stable across all regions. We also find that the $U2$ values in the post-event period are generally lower than in the pre-event period, indicating a decrease in the log of per-capita hours of wage supplement. This suggests a potential reduction in the unemployment rate. The data summary provided in Table 1 and in Appendix B also reveals that the number of council dismissals is exclusively positive within the treatment regions. The CD values in the post-event period are generally higher compared to the pre-event period, indicating an increase in the number of municipalities under compulsory administration. The change in these variables from 1992/1993 could potentially be attributed to stricter anti-Mafia measures implemented by the central government following the assassinations of Falcone and Borsellino, leading to more arrests for Mafia-related crimes. This provides further support for the proposition that these were the years of crisis that marked the beginning of a reinvigoration of the anti-Mafia movement in Italy (Calamunci et al., 2023; Schneider, 2018).

4 Methodology

This research aims to assess the influence of Mafia presence on public spending. To unravel this relationship, we employ a quasi-experimental analysis approach utilising two methods: the Difference-in-Differences method (Lechner et al., 2011) and the Synthetic Control Method (Abadie et al., 2015). In the subsequent sections, we provide detailed explanations of both methods and their underlying assumptions.

4.1 Difference-in-Differences

Some limitations of the 2-Stage Least Square method implemented by Acconcia et al. (2014) were that there might be an endogeneity issue because of unseen variables. Their research controls for a number of observable variables. However, there may be some unobserved factors that could be correlated with both Mafia presence and public spending which could bias the estimates. Using DiD helps address some of these endogeneity concerns by comparing changes in public spending before and after the assassinations of Falcone and Borsellino in the treatment group with changes in the control group. By comparing within-group changes over time, the DiD model helps to control for unobserved time-varying factors. Similarly, it addresses time-invariant heterogeneity.

Another contribution of using the DiD methodology is increasing the generalisability. By extending the same dataset with the DiD method, the study increases the comparability of results across different settings and time periods. And finally, the last and most important advantage of using DiD is that it provides a causal interpretation of the effect of the associations on public spending by isolating the impact of the event in the treatment group. DiD is popular in empirical economics and is used often to estimate the effect of policy changes that do not affect everybody at the same time and in the same manner. Lechner et al. (2011) explain this in their research and add that compared to, for example, regular matching methods, the DiD methodology has the big advantage that there is no need to control for all confounding variables.

For DiD to work, there needs to be a clear intervention or event that makes the treatment group distinct from the control group. The event of interest in our research is the assassinations of Falcone and Borsellino in 1992. The chosen regions for the treatment group are Sicilia, Calabria, Campania and Puglia. These states are chosen because they are known to host (the biggest) Mafia families in Italy (Acconcia et al., 2014; Draghi, 2011). Sicilia was also the region where Giovanni Falcone and Paolo Borsellino were the most active and subsequently murdered. It is anticipated that these prominent Mafia regions would be most significantly impacted by the implementation of stringent anti-Mafia measures subsequent to the assassinations. The control group for the DiD regression is composed of all other municipalities in Italy. A DiD analysis is employed to compare changes in public spending before and after the assassinations in the treatment group to changes in public spending in the control group. The following regression model is estimated and is based on the methodology described by Angrist and Pischke (2009); Zhang et al. (2021):

$$\begin{aligned} Public\,Spending_{i,t} = \beta_0 + \beta_1 * Treatment_{i,t} + \beta_2 * Post\_event_{i,t} \\ + \beta_3 * (Treatment_{i,t} * Post\_event_{i,t}) + \beta_4 * Controls_{i,t} + \mu_{i,t}, \quad (1) \end{aligned}$$

where the dependent variable is denoted by $Public\,Spending_{i,t}$, representing the level of public spending in municipality i during year t. The variable $Treatment_{i,t}$ serves as an indicator variable, distinguishing observations from municipalities with a high presence of Mafia (the treatment group). Additionally, we employ the variable $Post\_event_{i,t}$, an indicator variable denoting the year of the assassinations of Giovanni Falcone and Paolo Borsellino (1992). This variable helps identify whether an observation is considered "treated" or not. To capture the differential effect of the assassinations on public spending, we include an interaction term $Treatment_{i,t} \times Post\_event_{i,t}$. This term allows us to assess how the presence of the Mafia influences public spending in treatment regions during the period following the assassinations.

Furthermore, our model incorporates additional control variables denoted as $Controls_{i,t}$. These variables may include factors such as the unemployment rate, the number of council dismissals, lagged public spending variables etc., which are deemed relevant in the analysis.

The intercept, represented by β_0, indicates the expected value of public spending in municipalities with low Mafia presence before the occurrence of the assassinations. This serves as the baseline level of public spending for the control group.

Furthermore, the coefficient β_1 captures the average effect of Mafia presence on public spending in the absence of assassinations. On the other hand, β_2 encapsulates the impact of the assassinations on public spending across the low Mafia presence/control groups. The treatment effect on the treatment group can be found by summing up β_3 and β_2.

We would like to investigate whether there is a difference in public spending between the post-event control group and the post-event treatment group. We do this by calculating the Average Treatment Effect on the Treated (ATET) in period t which is defined by Lechner et al. (2011) as:

$$\begin{aligned} ATET_t &= E(G_t^1 - G_t^0 | Post - event = 1) \\ &= E_{X|Post-event=1}\theta_t(x) \end{aligned} \tag{2}$$

Here we calculate ATET by differencing the average treatment effect on the public spending variable G between the control and treatment group after the event has happened. The $\theta_t(x)$ then denotes the corresponding effects in the respective subgroups. $G_t^{Post-event}$ denotes the public outcome variable that would be expected for the different values of *Post-Event* in period t.

4.1.1 Assumptions for Difference-in-Differences

To ensure the validity of the DiD estimator, several key assumptions need to be satisfied (Columbia University Irving Medical Center, 2023). First of all, the treatment and outcome should be unrelated at the baseline meaning that the allocation of the treatment should not be determined by the outcome being studied. This can be explained using the following expression (Lechner et al., 2011):

$$E(G_1^1|X = x, D = 1) - E(G_0^0|X = x, D = 1) = E(G_1^0|X = x) - E(G_0^0|X = x) \tag{3}$$

This common trend or unrelatedness assumption ensures that any discrepancies observed in the outcome between the treatment and control groups are solely attributed to the treatment itself, rather than pre-existing differences. The expected outcomes for the control group over time (conditional on X) should be independent of being part of the treated group in the post-treatment period. If the event has not occurred yet, both subpopulations should experience the same time trends conditional on some observable variables X.

In our case, the unrelatedness assumption or the common trend assumption means that the allocation of the treatment (being in a region with a high Mafia presence) should not be determined by the outcome variable we are studying (public spending). From looking at the data in Appendix B, the unrelatedness assumption is likely to not hold. The average value of the public spending variable G in the treatment group is -0.454, whereas it is only -0.154 in the control group. This disparity raises the question of whether the level of public spending could potentially be a contributing factor to the high presence of the Mafia. If the common trend assumption is violated, it implies that there are systematic differences in the observed trends of the treatment and control groups even before the treatment is introduced. It then becomes challenging to isolate the true causal effect of the treatment which can introduce bias into the estimation of the treatment effect and should be taken into account when interpreting the results.

Secondly, it is essential to establish parallel trends between the treatment and control groups. This means that the two groups should exhibit similar patterns and trends before the implementation of the treatment, ensuring a comparable baseline. This assumption implies that, in the absence of the treatment, both groups would have followed a similar trajectory (Abadie, 2005). It ensures that any differences observed after the treatment can be attributed to the treatment effect rather than pre-existing divergences. To examine the parallel trend assumption, we conduct a Chow (1984) test by comparing the regression coefficients before and after a specific breakpoint, which in this case are the assassinations of 1992. This analysis allows us to assess the potential divergence between the pre-treatment and post-treatment trends and determine whether there is a significant change between the two groups. We find that there is no significant difference between the pre-and post-treatment trends as the Chow statistic is not significant ($5.46 \times 10^{-}6$), which suggests that the assumption of parallel trends is adequately met.

To strengthen our assumption of parallel trends, we conducted balance checks (White and Sabarwal, 2014) on the covariates within the DiD estimation. These checks are essential to ensure that the covariates between the treatment and control groups are balanced, validating that there are no systematic differences in observed characteristics. Balanced covariates indicate that any treatment outcomes can be more confidently attributed to the treatment itself, thereby reinforcing the strength and validity of our inference (Atanasov and Black, 2021; White and Sabarwal, 2014). When examining the covariates' balance in the baseline regression, we found that only the CD variables exhibited a significant difference between the treatment and control groups. However, we consider these findings reasonable because one of our criteria for selecting the treatment group was their prior number of council dismissals, which indicated a high presence of Mafia activity. Fortunately, all other covariates showed no signs of imbalance. Prior literature suggests that Multivariate Matching Methods can be employed to mitigate the need for the parallel trend assumption (Diamond and Sekhon, 2013; O'Neill et al., 2016). These methods aim to balance the treatment and control groups based on pre-treatment covariates (Kreif et al., 2016; Steventon et al., 2013). However, given our already balanced data, we believe that this supports the reasonable satisfaction of the parallel trend assumption.

Next is the assumption that there is stability in the composition of treatment and control groups. Any significant differences in the composition of the groups could introduce confounding factors that affect the estimated treatment effect. To assess this assumption, we investigate the change in the variables $Murder$, $Mafiosi$, CD, $Extortion$ and $Corruption$ which are all related to the composition of a region. $Mafiosi$, $Murder$, $Extortion$ and $Corruption$ are all the first differenced numbers of arrests related to their respective Mafia-associated arrest. Based on the data summary provided in Appendix B, we can deduce that the mentioned variables exhibit minimal variation between the pre-and post-treatment periods. This observation suggests that the assumption of a consistent composition within the groups can be reasonably upheld.

Finally, it is important to consider the assumption of spillover effects. Spillover effects occur when the changes resulting from the treatment extend beyond the treated group and affect the control group's outcomes. Due to the national unification efforts to combat the Mafia (Calamunci et al., 2023; Paoli, 2007; Schneider, 2018), this assumption might not hold. For instance, Galletta (2017) explains that regional anti-Mafia measures, specifically council dismissals, implemented between 1998 and 2013 led to a decrease in public investment in neighbouring municipalities. This suggests that the increase in public spending in one region might be influenced by spillover effects. However, Acconcia et al. (2014) found no significant spillovers of provincial spending into adjacent areas for the data used in our study, indicating that local economies may be relatively insular. We also replicate part of the results of Acconcia et al. (2014) in Table 13 located in Appendix A, which supports their findings. The difference in the findings might stem from the autoregressive nature of policy implementations (Calamunci et al., 2023). While it remains ambiguous to conclusively determine if the spillover assumption is entirely satisfied, we believe that the available evidence suggests that there are no significant spillover effects observed during the period spanning from 1987 to 1999.

4.2 Synthetic Control Method

One notable limitation of the DiD methodology in our study is the potential violation of the common trend assumption. When this assumption is not satisfied, the estimated treatment effects may fail to accurately capture the true causal effects of the treatment. To assess the robustness of the DiD results, we propose employing an SCM. By utilising this approach, we can address the violation of the common trend assumption and obtain more reliable estimates of the treatment's causal effects. By comparing the results obtained from both the DiD and the SCM, we can determine if they yield similar estimation outcomes. If the two methods provide consistent results, it enhances our confidence in the robustness of the DiD findings.

According to Xu (2017), there are two widely known matching methods for conditioning on pre-event observations. The author explains that these matching methods help balance the influence of potential time-varying confounders between the treatment and control groups and help alleviate parallel/common trend issues. Additionally, Chabé-Ferret (2014) also discusses the effectiveness of combining regular matching methods and DiD estimations. However, as Xu (2017) explains, regular matching methods do not always guarantee parallel or common trends. Therefore, the SCM proposed by Abadie et al. (2015); Abadie and Gardeazabal (2003) might be a more appropriate approach to address the common trend assumption.

SCMs offer a valuable approach for constructing a comparison group in a DiD analysis, which closely resembles the treated group, as emphasised by Abadie et al. (2010). The authors particularly highlight how synthetic comparison units can be used in comparative case studies, including the present study. The underlying concept of SCMs involves creating a weighted combination of control units that replicates the pre-event characteristics of the treated group. This Synthetic Control unit serves as a counterfactual or "synthetic" control group against which the post-treatment outcomes of the treated unit can be compared (Abadie et al., 2010; Becker et al., 2021). The Synthetic Control approach acknowledges that a combination of units often yields better comparisons than examining any single unit alone, as discussed by Abadie et al. (2010).

4.2.1 Potential Synthetic Control Units

In this study, we applied an SCM by identifying regions that could be utilised to generate Synthetic Controls, known as potential control units. These potential control units have to exhibit similarities to the treated region in terms of pre-event characteristics. The selected areas for the Synthetic Control groups are Basilicata, Friuli Venezia Giulia and Marche. Please refer to Appendix B for the complete descriptive statistics table. In this table, the initial four rows show the treatment states. It is noteworthy that the variable representing public spending denoted as G, exhibits a consistent negative trend in the treated regions. The magnitudes of this variable range from -0.148 to -0.659, indicating substantial reductions. Based on this criterion of significantly negative pre-event G values, we have identified Basilicata, Friuli Venezia Giulia, and Marche as suitable control units. Although we considered Molise as a potential control unit, we discovered that the average pre-event G magnitude (-1.482) of Molise was too large, which could potentially skew the results and introduce risks. Additionally, Molise exhibited higher magnitudes for the $U1$ and $U2$ outputs, whereas the selected regions showed more comparable values. We did not find any other trends in the treatment variables that could have resulted in the inclusion of additional potential Synthetic Controls.

The process of constructing the Synthetic Control unit involves applying Mill's Method of Difference (Abadie et al., 2015; Podestà, 2023), which assigns weights to the control units in order to minimise the differences in pre-treatment characteristics between the treated unit and the Synthetic Control group (Abadie et al., 2015; Becker et al., 2021). This difference is denoted by

$$||X_1 - X_0||_v := \sqrt{(X_1 - X_0W)'V(X_1 - X_0W)}, \tag{4}$$

where the weights used to construct the Synthetic Control units are shown as W and the values of the predictor variables of the treatment group are given in matrix V (Becker and Klößner, 2018). The optimisation problem is therefore, given the weights of V, find an optimal set of W such that (Abadie et al., 2011; Becker and Klößner, 2018):

$$\sqrt{(X_1 - X_0W)'V(X_1 - X_0W)} \xrightarrow{W} min. \tag{5}$$

Estimating these weights can be done using various statistical techniques such as weighted least squares or Bayesian methods (Becker and Klößner, 2018). In our analysis, we chose to utilise a regression-based method to determine the variable weights (Galiani and Quistorff, 2017). This method relies on a constrained quadratic programming routine that identifies the optimally weighted combination of the regression-based V-matrix (Abadie et al., 2011). Additionally, we employed a nested optimisation procedure that searches among all positive semidefinite V-matrices and sets of weights to find the optimal convex combination. Although this nested optimisation procedure may take longer to compute, it results in an even lower Mean Squared

Prediction Error (MSPE). We do this nested optimisation three times and choose the weight with the lowest MSPE out of them. The first optimisation is done on the regression-based V-matrix, then on an equal weights V-matrix and the last one uses the STATA maximum likelihood search-matrix starting values (Abadie et al., 2011; Masi and Ricciuti, 2019).

Creating Synthetic Controls through a weighted combination of available control units offers significant advantages. It allows us to showcase the relative contribution of each control unit to the counterfactual and highlights the similarities between the group affected by the event and the Synthetic Control. Moreover, there is no need to be cautious about extrapolation biases, which are common concerns in regression-based analyses (King and Zeng, 2006). By using a weighted average of units as a comparison, the SCM avoids these biases and enables a more focused analysis of the differences (Abadie et al., 2015). SCMs offer several benefits. They enable the creation of a counterfactual control group that closely resembles the treated unit, even when natural control units are limited or unavailable. The SCM offers the flexibility for the effects of predictors to change over time while preserving the linear relationship between pre-treatment covariates and post-treatment outcomes (Kreif et al., 2016). However, its main advantage lies in eliminating the requirement for the common trend assumption in DiD analyses.

We calculated the Root Mean Squared Prediction Error (RMSPE) for the constructed Synthetic Control unit, which resulted in a value of 0.104. This value indicates the average difference between the actual outcome of the treated unit and the predicted outcome using the Synthetic Control which is quite low in our case. Additionally, we observed a reasonably balanced distribution of the predictor variable G between the treated unit and the Synthetic Control. The predictor balance table can be found in Appendix C. We also conducted an additional balance check on the covariates in the SCM. The purpose was to ensure the correct implementation of the method, which inherently balances control units based on pre-treatment outcomes (Ben-Michael et al., 2021). This analysis ultimately validated the appropriate implementation of the SCM, as it revealed no significant disparities between the covariates of the Synthetic Control group and the treatment group. Overall, based on the provided results, we can conclude that the SCM, utilising the selected regions, was successfully implemented, and the constructed Synthetic Control adequately captures the characteristics of the treated unit.

4.2.2 Synthetic Control Estimation

Once the Synthetic Control unit is constructed, we can compare the post-treatment outcomes of the treated unit with the Synthetic Control unit to evaluate the causal impact of Mafia presence on public investment. To incorporate the SCM into a DiD analysis we use the following equation:

$$G\_diff = \beta_0 + \beta_1 * Treatment\_post\_event + \beta_2 * Synth\_control\_post\_event + \gamma_1 * X + \epsilon. \quad (6)$$

In (6) we use the G_diff variable. This variable represents the difference in the outcome variable between the periods before and after the event for each observation in the analysis. The $Treatment\_post\_event$ variable represents the change in the outcome (G_diff) for the treated group during the post-event period in contrast to the pre-event period. Whereas $Synth\_control\_post\_event$ looks at the change in the outcome for the Synthetic Control group during the post-event period relative to their pre-event period. The $Treatment\_post\_event$ variable considers for each observation whether it belongs to the treated group and looks at whether the observation falls within the post-event period. The $Synthetic\_control\_post\_event$ variable does the same but looks at whether an observation belongs to the Synthetic Control group. β_0 is a constant and the X variable is a vector of controls that include CD, CD_S1, CD_S2, $Extortion$, $Mafiosi$, $Corruption1$, $Corruption2$, $Murder$, $U1$, $U2$ and lagged values of these variables.

4.2.3 Assumptions for the Synthetic Control Method

According to Bouttell et al. (2018), there are three key assumptions that underlie the use of the SCM. Firstly, it is crucial to acknowledge the requirement for high-quality data and the reasonable assumption that the pre-treatment characteristics adequately capture the treatment effects.

The second key assumption parallels the assumption of no-spillover effect in the DiD method. In line with the findings of Acconcia et al. (2014), we assume no significant evidence of spillover effects to neighbouring areas based on the data from 1987 to 1999.

The third key assumption is the absence of external shocks in the potential control units. In the context of our research, this implies that the Synthetic Control units did not experience any interventions, policy changes, or external events that could independently influence the outcome variable during the post-treatment period. To evaluate this assumption, we examine Table 1 in Section 3 and investigate historical information. Only Basilicata stands out with a notably higher post-treatment value for the output variable G compared to other regions. However, to the best of our knowledge, there are no reported external shocks known to have exclusively affected Basilicata, which could explain the remarkably positive post-treatment public spending value in the region. Therefore we assume that there were no external shocks present in the potential control units.

4.3 Robustness Checks

We conduct similar robustness checks for both methods to enhance the validity of our results. The two methods already serve as robustness checks for each other, providing additional confidence in the relationship between the independent and dependent variables. In addition to this, we extend our set of regressors as a form of sensitivity analysis.

In our first regression, we incorporate the lagged variable of public spending G. Moving to the second regression, we expand the model by including lagged G and (lagged) Y values. Here, Y represents the percentage growth rate of real per-capita total value added. In the third regression, we extend the model further by incorporating (lagged) values of G, Y and SG. The variable SG represents the per capita investment in provinces within the same region, excluding the province itself. Finally, in our last regression, we introduce an interaction term between the one-period lagged G and the one-period lagged SG. This interaction term, known as the spillover term, helps us assess the potential complementarity or substitutability between spending in neighbouring areas, as observed in Acconcia et al. (2014).

We employed the Wooldridge (2010) serial correlation test, to investigate whether our regressions violated the assumption of no autocorrelation. This commonly used test detects serial correlation in linear panel-data estimations and was implemented following the procedure outlined by Drukker (2003). Based on our analysis, we identified the presence of autocorrelation in both our DiD and SCM models. In order to mitigate this issue, we apply robust standard errors in all of our regressions. The use of robust standard errors allows us to calculate robust t-statistics, which determine the statistical significance of the coefficients. This approach addresses violations of the assumptions of homoscedasticity and autocorrelation (Croux et al., 2004), ultimately improving the reliability of hypothesis testing.

Furthermore, we test for multicollinearity using the Variance Inflation Factor (VIF) test (Freund et al., 2003). The VIF test measures the inflation of the variance of an estimated coefficient due to multicollinearity as explained by Robinson and Schumacker (2009). Higher VIF values indicate higher levels of multicollinearity. In our assessment, we consider a threshold of 10 to determine the presence of multicollinearity (Belsley et al., 2005; Robinson and Schumacker, 2009; Wan et al., 2019). This test helps ensure the independence of our regressors and enhances the validity of our results (Sanders et al., 2022).

After conducting the Synthetic Control estimation, we proceed with a Placebo test to assess the magnitude of the estimated effects of the actual intervention compared to those of a placebo treatment group (Abadie et al., 2010). In line with Abadie et al. (2010), we employ the Mean Squared Prediction Error (MSPE) to perform this test. The placebo treatment group consists of regions prior to the assassinations of the anti-Mafia judges in 1992. We reject the null hypothesis of no intervention effect when the MSPE of the actual Synthetic Control estimation is larger than that of the placebo treatment group (Ferman and Pinto, 2017). If the null hypothesis is rejected, it suggests that the results obtained from our Synthetic Control estimation are not affected by a placebo effect.

It is important to note that recent studies have highlighted certain limitations of placebo tests, raising concerns about their validity and the need for caution when interpreting the results. Research conducted by Hahn and Shi (2017) has identified potential distortions in the size of the permutation (placebo) test, which can undermine its effectiveness as a tool for inference with the SCM. This finding is further supported by Ferman and Pinto (2017), who emphasises that the graphical analysis of placebo tests, as suggested by Abadie et al. (2010), can be misleading. Even when the test is based on the MSPE, there is a possibility of some distortions in its size. While it is essential to exercise caution when interpreting the results of the placebo test, it is still valuable to proceed with its implementation to gain insights and ensure adherence to established practices.

5 Results

5.1 Key Findings of "*Mafia and Public Spending: Evidence on the Fiscal Multiplier from a Quasi-Experiment*"

This research builds upon the work of Acconcia et al. (2014), which examines the consequences of laws targeting political corruption and Mafia infiltration in city councils. The previous study reveals significant temporary contractions in local public spending resulting from these measures. Using 2-Stage Least Square estimations, they find that the output multiplier for public spending cuts at the provincial level is 1.5. Moreover, considering lagged spending as exogenous to current output, the overall multiplier increases to 1.9. Their study suggests that anti-Mafia laws exert an influence on public spending, with the number of council dismissals serving as an instrument to assess the impact of these dismissals.

Table 2: OLS and 2-Stage Least Squares results of Acconcia et al. (2014)

	OLS	OLS (including lagged Y)	First stage	Second stage	First stage (including lagged Y)	Second stage (including lagged Y)
G(t)	0.21**	0.23**		1.46**		1.55***
	(0.07)	(0.07)		(0.49)		(0.43)
G(t-1)	0.22**	0.26**	-0.41***	0.73***	-0.41***	0.79***
	(0.08)	(0.08)	(0.07)	(0.21)	(0.07)	(0.19)
G(t-2)	0.00	0.04	-0.13*	0.14	-0.13*	0.19
	(0.07)	(0.07)	(0.06)	(0.11)	(0.06)	(0.11)
Y(t-1)		-0.16*			0.03	-0.20**
		(0.06)			(0.02)	(0.06)
Y(t-2)		-0.03			-0.02	-0.02
		(0.05)			(0.02)	(0.05)
Ftest_instruments			12.58		11.83	

Notes: $G(t)$ represents the year-on-year change in per capita real infrastructure investment divided by the previous year's per capita real value added. Lagged values $G(t-1)$ and $G(t-2)$ are included as one-period and two-period lags, respectively. Y represents the percentage growth rate of real per-capita total value added. The robust standard errors are reported in the brackets. The significance is denoted as follows:
* Significant at the 5 percent level.
** Significant at the 1 percent level.
*** Significant at the 0.1 percent level.

We aimed to verify the robustness of their findings and have replicated their results, which are summarised in Table 2. The first two columns present the OLS estimates, demonstrating coefficients and significance consistent with those reported by Acconcia et al. (2014). Notably, the estimated impact multiplier remains at 0.2.

Moving to the IV estimation models, the last four columns of the table display the results of the 2-SLS estimations. These models were conducted with and without lagged values of the variable Y. The third and fifth columns present the outcomes of the first-stage regressions, indicating that provinces undergoing council dismissals experience substantial declines in public investment, as evidenced by the negatively significant coefficients of G. The strength of the two instruments used is consistent with that reported by Acconcia et al. (2014), with values of 12.58 and 11.83, respectively. In the second-stage regression, we observe that the point estimate for contemporaneous spending (excluding lagged output) is 1.46, while the overall point estimate is 1.55. This suggests that a 1 percent reduction in local public infrastructure, relative to local value-added, leads to a contemporaneous spending reduction of about 1.5 percent. Importantly, the coefficient for contemporaneous spending is significantly different from zero in both versions of the model. This discrepancy between the OLS and IV estimates of contemporaneous spending is consistent with the findings of Acconcia et al. (2014), indicating a downward bias in the OLS estimates. Assuming exogeneity of lagged spending with respect to current output, the overall point estimate, including lagged Y values, is determined to be 1.93. This estimate is derived by summing the contemporaneous spending variable $G(t)$ with its one-period lagged value and taking into account the influence of the first lag of the dependent variable in the first stage. These results indicate that anti-Mafia legislation, specifically compulsory council dismissals, resulted in a temporary decrease in public spending. Additionally, when examining the exclusion restriction outlined in Appendix A for the 2-Stage Least Squares estimation, Acconcia et al. (2014) suggested that Mafia activity could potentially suppress economic activity during council dismissals. Our investigation aims to examine the validity of this finding in a broader context, extending beyond the specific scenario of council dismissals.

5.2 Difference-in-Differences Results

Table 3: DiD estimations

G	(1)	(2)	(3)	(4)
Treatment Pre-event	0.043 (0.312)	-0.069 (0.318)	-0.095 (0.320)	-0.063 (0.319)
Post-event	0.011 (0.114)	-0.022 (0.119)	-0.034 (0.120)	-0.020 (0.121)
Treatment x Post event	-0.071 (0.338)	0.071 (0.344)	0.125 (0.346)	0.064 (0.345)
G(t-1)	-0.429*** (0.086)	-0.442*** (0.085)	-0.445*** (0.084)	-0.441*** (0.084)
G(t-2)	-0.130* (0.061)	-0.137*** (0.062)	-0.132* (0.061)	-0.143* (0.062)
Y(t)		0.059* (0.025)	0.042 (0.022)	0.059* (0.025)
Y(t-1)		0.041 (0.023)	0.039 (0.023)	0.043 (0.023)
Y(t-2)		-0.011 (0.023)	-0.003 (0.022)	-0.012 (0.023)
SG(t)			0.298*** (0.081)	
SG(t-1)			0.190 (0.102)	
G(t-1) x SG(t-1)				-0.056 (0.077)
Constant	0.005 (0.108)	0.030 (0.112)	0.037 (0.112)	0.028 (0.114)
Observations	855	855	855	855

Notes: Here, G represents the year-on-year percentage change of real per-capita public investment in infrastructure. Column 1 displays the results of a regression that exclusively utilises lagged variables of G. Moving to column 2, we extend the analysis by including variable Y and its lagged values, which capture the percentage growth rate of real per-capita total value added. Expanding further in column 3 where the variable SG is introduced. The variable SG measures the year-on-year percentage change of real per-capita public investment within provinces belonging to the same region. Finally, column 4 incorporates an interaction term between the lagged value of G and SG. The *Treatment pre-event* variable shows how the control and the treatment group differ from each other in terms of the output variable G before the assassinations. The *Post-event* variable shows the average treatment effect for the control group. The *Treatment* $\times$ *Post-event* interaction term helps determine the treatment effect for the treatment group. The robust standard errors are reported in the brackets. The significance is denoted as follows:
* Significant at the 5 percent level.
** Significant at the 1 percent level.
*** Significant at the 0.1 percent level.

Upon analysing the DiD regressions in Table 3, specifically focusing on the treatment group comprising Sicilia, Calabria, Campania and Puglia, it is observed that the coefficient associated with the variable $Treatment$ lacks statistical significance. This variable represents the disparity between the treated and control groups before the event occurred. The lack of significance suggests that, on average, there is no substantial difference between the treatment and control groups in terms of the outcome variable G during the pre-event period. This result remains consistent across all columns where different control variables are added, indicating robustness in the insignificance of the $Treatment$ *Pre-event* variable. The variable *Post-event* represents the average treatment effect on the outcome variable during the post-event period, relative to the pre-event period, specifically for the control group. Our analysis reveals positive effects. However, these effects lack statistical significance. This indicates that, on average, there is no significant difference in the outcome variable G between the post-treatment and pre-treatment periods for the control group. Importantly, this insignificance remains consistent across the other regression iterations as well. We also find that the differential impact of the event on the outcome variable G for the treatment group, captured by the combined effect of the interaction term $Treatment$ $\times$ *Post-event* and the variable *Post-event*, was statistically insignificant.

The ATET is calculated by taking the difference between the average outcome of the treatment group after the event and the average outcome of the control group after the event. The ATET is -0.028 in the baseline regression which can be seen from summing up $Treatment$ and $Treatment \times$ *Post-event*. However due, to the insignificance of the variables, we also conclude that the ATET is not significantly different from zero. These findings, combined with the aforementioned results, suggest that the assassinations of the two anti-Mafia judges did not lead to a significant change in public spending.

It is worth noting that the lagged values of G exhibit statistical negativity, suggesting that previous levels of public spending have a downward impact on current public spending. In other words, when public spending increases in the past, it tends to decrease in the present, highlighting the autoregressive nature of public spending. This characteristic implies that short-term observations and long-term outcomes may differ. Importantly, this finding remains consistent even after incorporating additional regressors.

In columns 2 to 4, the analysis includes lagged values of the variable Y, which represents the percentage growth rate of real per-capita total value added. The $Y(t)$ variable is significant in the second and fourth columns. The lagged values of Y are all insignificant. This suggests that the growth rate of total real capita value added has an impact on public spending. However, the significance of $Y(t)$ diminishes when the variable SG is included in column 3. The SG variable compares the investment in provinces within the same region, excluding the province being analysed, to the lagged real per capita value. In this case, the previously significant variable $Y(t)$ becomes insignificant, while the $SG(t)$ variable is significant. This finding suggests that there is an interconnected relationship between Y, SG, and the dependent variable G. It implies that the year-on-year change of real per-capita public investment within the same region (SG) plays a more dominant role in explaining the variations in public investment compared to the growth rate of total value added alone ($Y(t)$).

Furthermore, in the fourth column, we introduce an interaction term involving the lagged variables $G(t-1)$ and $SG(t-1)$ to assess the extent of the potential spillover effect. However, this interaction term is found to be insignificant, indicating that there is no evidence of a significant spillover effect. The inclusion of this variable does not substantially impact the significance or magnitude of the results.

5.3 Synthetic Control Estimation Results

In the Synthetic Control estimation, we utilise the variable G_diff, which measures the difference in the outcome variable between the periods before and after the event for each observation in the analysis. The variable G_diff incorporates the Synthetic Control weights calculated for the regions Basilicata, Friuli Venezia Giulia and Marche which are 0.135, 0.028, and 0.827, respectively. The results of this estimation are presented in Table 4. Similar to regular DiD estimation, we expand the set of predictors to include potential influential control variables to see whether these specific control variables have an impact on the outcome.

The interaction term between the treatment and post-event period, denoted as $Treatment$ x *Post-event* signifies the change in the outcome (G_diff) for the treated group during the post-event period compared to the pre-event period. The coefficient of 0.189 in the first column

Table 4: Estimation results of the Synthetic Control Method

G_diff	(1)	(2)	(3)	(4)
Treatment post event	0.189	0.180	0.114	0.182
	(0.399)	(0.327)	(0.387)	(0.342)
Synth control post event	0.434	0.330	0.289	0.329
	(0.522)	(0.447)	(0.513)	(0.455)
G(t-1)	0.202	0.296	1.516	0.329
	(0.389)	(0.416)	(2.178)	(0.618)
G(t-2)	0.196	0.203	0.333	0.211
	(0.415)	(0.447)	(0.511)	(0.490)
Y(t)		-0.144	-0.157	-0.140
		(0.181)	(0.214)	(0.200)
Y(t-1)		0.144	0.099	0.152
		(0.138)	(0.166)	(0.183)
Y(t-2)		0.136	0.122	0.139
		(0.151)	(0.163)	(0.161)
SG(t)			0.139	
			(0.521)	
SG(t-1)			-1.188	
			(2.092)	
G(t-1) x SG(t-1)				-0.017
				(0.202)
Constant	-0.263	-0.184	-0.145	-0.183
	(0.417)	(0.336)	(0.378)	(0.340)
Observations	54	54	54	54

Notes: This table summarises the impact of assassinations in 1992 using a Synthetic Control group. The control variables used are the same as the ones used in Table 3. We regress now on the output variable G_Diff which measures the difference in G between the periods before and after the event for each unit in the analysis. The robust standard errors are reported in the brackets. The significance is denoted as follows:
* Significant at the 5 percent level.
** Significant at the 1 percent level.
*** Significant at the 0.1 percent level.

implies that, on average, the treated group experienced a positive change of 0.189 units in the outcome during the post-event period, while accounting for other variables in the model. However, this coefficient is not statistically significant, indicating that there is insufficient evidence to conclude that the treatment had a noticeable effect on the outcome of this analysis. Therefore, it suggests that the assassinations of the anti-Mafia judges in 1992 did not have a significant impact on public spending. The expansions of the set of regressors support the consistency of this finding. It is observed that, in general, the inclusion of these control variables reduces the coefficient's value and also reduces its variance.

Upon examining the coefficient of the *Synth control* x *Post-event* variable in all iterations of the estimations, we find that it is consistently positive but insignificant. This variable measures the change in the outcome for the Synthetic Control group during the post-event period compared to the pre-event period. The results indicate that, on average, the Synthetic Control group did not experience any significant change in the outcome during the post-event period relative to the pre-event period. These results indicate that factors other than the treatment, such as control variables and inherent characteristics of the Synthetic Control group, had minimal impact on the outcome. Therefore, these findings suggest a low likelihood of alternative factors influencing the outcome during the post-event period. Moreover, these findings align with the results obtained from the *Treatment* x *Post-event* variable, providing evidence that the assassinations in 1992 did not have a significant impact on public spending. This implies that the immediate impact of changes in Mafia presence on public spending is minimal overall.

Contrary to the results presented in Table 3, we find that the two-period lagged $G(t-2)$ variable demonstrates no significance in the SCM estimations. This raises an interesting question regarding potential long-term effects that are not observed within the scope of this study, necessitating further investigation to draw a comprehensive conclusion.

The addition of extra regressors in the SCM regressions did not alter the significance of the coefficients. Specifically, the inclusion of the variable SG did not affect the significance of the variable Y in this analysis. This suggests that the impact of within-province public investment on the outcome variable is independent of the within-province public spending component discussed earlier. Furthermore, the inclusion of the interaction term $SG(t-1) \times G(t-1)$, previously referred to as the spillover term, also does not exhibit any significant differences, providing further evidence that there is likely no spillover effect present.

Upon conducting the Variance Inflation Factor (VIF) test, we have determined that the mean VIF score for almost all of our regressions does not exceed 10. These findings indicate that there is no significant multicollinearity problem among the predictor variables. Specifically, the average VIF scores for the DiD and Synthetic Control regressions including (lagged) Y values are 2.03 and 5.66, respectively. The results of this test can be found in Appendix D. This means that our research findings provide strong evidence that multicollinearity is not a significant concern in our study.

Additionally, based on the results of the placebo test, we find no evidence of a placebo effect. This further strengthens the robustness of our findings and suggests that the estimated effects of the actual intervention are significantly larger compared to the effects observed in a randomly assigned placebo treatment group (Abadie et al., 2010). In conclusion, our findings from the DiD analysis and the SCM consistently indicate that the assassinations of the anti-Mafia judges Giovanni Falcone and Paolo Borsellino in 1992 had no (immediate) significant impact on public spending in Italy. These results highlight the robustness of our findings and support the conclusion that Mafia presence does not establish a causal relationship with public spending.

6 Conclusion

The objective of this study was to examine the causal relationship between Mafia presence and public spending in Italy. Specifically, we sought to investigate whether the assassinations of two anti-Mafia judges, Giovanni Falcone and Paolo Borsellino, in 1992 had a notable impact on public spending in regions with a high presence of Mafia activity. To accomplish this, we employed both the DiD method and an SCM analysis.

Our analysis revealed no substantial evidence supporting the notion that the assassinations had an immediate effect on public spending in the affected regions. Notably, both the DiD estimation and Synthetic Control estimation yielded consistent results, indicating the robustness of our findings. Furthermore, expanding our set of regressors did not alter these conclusions, thereby reinforcing their reliability.

The implications of our results hold significance for policymakers aiming to prioritise the growth of public spending. It may appear paradoxical, but efforts to combat the Mafia can temporarily diminish public spending. Consequently, policymakers may need to reconsider their approach to boosting public spending. Instead of solely focusing on combating the Mafia, redirecting attention towards addressing other potential obstacles that hinder the growth of public spending could yield more fruitful results.

This paper possesses several limitations that warrant discussion. Firstly, the research relies solely on data from 1987 to 1999, which restricts the representativeness of the findings and inhibits drawing conclusions about long-term effects. Policy implementations typically exhibit an autoregressive nature (Calamunci et al., 2023), implying that the effects of policy actions following the assassinations of the two anti-Mafia judges may not manifest immediately. To establish a comprehensive understanding and determine any causal relationship between Mafia presence and public spending, a broader observation period is necessary to account for long-term effects.

Secondly, both methods employed in this study are contingent upon the assumption of no-spillover effects. Spillover effects occur when changes resulting from the treatment extend beyond the treated group and influence outcomes in the control group. Although this assumption was considered to be satisfied based on the findings of the paper by Acconcia et al. (2014) and the replication of their results in our study, the research conducted by Galletta (2017) introduces a contrasting perspective. He argues that regional anti-Mafia measures, particularly council dismissals, led to a decrease in public investment in neighbouring municipalities due to law enforcement spillovers that effectively reduced illicit activities in those areas. The use of data from different time periods (1998 to 2013) could be the reason for the different outcomes. Consequently, the fulfilment of the no-spillover assumption remains ambiguous, necessitating further research to provide a definitive answer.

Another important aspect to consider is that we propose that the assassinations of the two anti-Mafia judges in 1992 was a pivotal event that triggered a transformation in the level of Mafia presence in Italy. This assertion is based on our observation of the subsequent implementation of new legislation aimed at combating the Mafia. We argue that the assassinations of Giovanni Falcone and Paolo Borsellino played a role, both directly and indirectly, in initiating the decline of the Mafia's influence. Nevertheless, it is possible to argue that the connection between the assassinations and the emergence/reinvigoration of the anti-Mafia movement may not be as strongly correlated as we claim. Further investigation is needed to evaluate the significance of this relationship.

We acknowledge that our research has several limitations. However, the consistency of our findings across various estimation methods and the robustness of our results support the conclusion that Mafia presence does not play a causal role in public spending dynamics. According to the findings, while the Mafia's presence may have some influence on specific aspects of public life, it appears that it is not the primary driving factor behind public spending. Prior studies, including the research that serves as the foundation for this article (Acconcia et al., 2014), have indicated that anti-Mafia measures, particularly compulsory council dismissals, led to a decline in public spending. Nevertheless, our findings challenge the notion of a causal association between Mafia presence and public spending. The observed effect on public expenditure is likely to have arisen through an alternative pathway rather than directly due to changes in Mafia presence.

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A Appendix A: Replication

The replication of Acconcia et al. (2014) was done using the provided replication package. We conduct a replication to ensure the validity and reliability of the original study's findings. It was also done to get a comprehensive understanding of the results and to see potential issues or limitations we could expand on. The definitions of the variables used in the analysis are obtained from Acconcia et al. (2014) and taken from their readme file, which is included in their replication package.

A.1 Calculating Mean Differences

To replicate the study conducted by Acconcia et al. (2014), the initial step involves assessing the mean differences in investment spending following a council dismissal. This analysis compares changes in public investment between provinces that experienced a council dismissal and those that did not, as presented in Table 5. The treatment group consists of all province-year observations occurring in the first calendar year after a council dismissal. This group is identified by the variable $Split\_CD\_NoCD$, which is restricted to the years 1989-1999 and takes a value of 1 when a council dismissal occurred. Additionally, we generate a lagged version of this variable, denoted as $lSplit\_CD\_NoCD$, which represents the observations that occurred one year prior to the council dismissal.

The analysis presented in Table 5 involves comparing mean differences in various variables between different groups. The control group in the first two columns consists of the remaining sample not included in the treatment group. In columns 3 and 4, a control group consisting of provinces without any government dismissals is used. Columns 5 and 6 compare the differences between these two control groups. To compute the mean differences, several t-tests are conducted. Column 1 focuses on the variable *Gprop*, which represents the percentage growth rate of real per capita public investment. An unequal variance t-test is used to compare the means of the *Gprop* variable based on different values of the $lSplit\_CD\_NoCD$ variable. Similar t-tests are performed in columns 2, 4, and 6, but using the variable G instead of *Gprop*. The variable G captures the year-on-year percentage change of real per capita public investment as a ratio of lagged real per capita value added.

Table 5: Mean difference

	(1)	(2)	(3)	(4)	(5)	(6)
Mean difference	-19.651***	-0.460**	-23.760***	-0.495*	-4.723	-0.041
	(5.356)	(0.195)	(7.118)	(0.258)	(5.294)	(0.177)
Observations	950	950	180	180	905	905

Notes: Columns 1-4 of the table present mean difference results for changes in public investment between the treatment and control groups. Columns 5 and 6 show the changes in public investment for two different control groups. The outcome variable G is expressed as a percentage of either lagged investment (columns 1, 3, and 5) or lagged value added (columns 2, 4, and 6). The treatment group refers to observations in the first year after a council dismissal. The control group in columns 1 and 2 includes all remaining observations not in the treatment group, while the control group in columns 3 and 4 consists only of observations that have previously undergone a council dismissal. The robust standard errors are reported in the brackets. The significance is denoted as follows:
* Significant at the 5 percent level.
** Significant at the 1 percent level.
*** Significant at the 0.1 percent level.

A.2 The Impact of Initial Council Dismissals

The next objective is to evaluate the impact of an initial council dismissal on the growth rate of real per capita added. This section seeks to investigate whether there are variations in growth rates before and after council dismissals and whether the average growth rates of treated provinces differ from the rest of the sample. The objective is to ascertain if the implementation of council dismissals is consistently linked to local economic activity. To achieve this, an OLS regression is performed and its results are examined and interpreted. The regression equation is formulated as follows:

$$Y_{i,t} = \gamma_0 + \gamma_1 * D_{i,t} + \gamma_2 * t + \gamma 3 * (t \times D_{i,t}) + \phi_{i,t}. \tag{7}$$

The regression model includes a time trend t and a dummy variable $D_{i,t}$ that takes the value of 1 for observations before the first council dismissal and 0 otherwise. The coefficients of interest in the model are γ_1 and γ_3. The coefficient γ_1 helps determine if there is a difference in the average growth rate between treated provinces and the rest of the sample. On the other hand, γ_3 indicates whether there is a distinct trend prior to the first council dismissal.

Table 6 shows the results of the OLS regression. The insignificant and small coefficient of γ_3 implies that there is no differential trend in growth rates before the first council dismissal, consistent with the findings of Acconcia et al. (2014). Moreover, the insignificant coefficient of the γ_1 variable confirms that the average growth rate in treated provinces is not different from the rest of the sample.

Table 6: Did average growth change after the first compulsory dismissal?

	(1) Y
Average growth rate disparity between treated and control groups	0.26
	(0.79)
Differential growth rate trend pre-Council Dismissal	-0.07
	(0.19)
Observations	1330

Notes: The robust standard errors are reported in the brackets. The significance is denoted as follows:
* Significant at the 5 percent level.
** Significant at the 1 percent level.
*** Significant at the 0.1 percent level.

A.3 Generating the Regressors

In essence, we create several new regressors by making lagged versions of various variables such as CD, CD_s2, $Resignation$, $Election$, $Budget$, G, Y and $Others$. We then calculate the mean value of the variables $L1G$ and $SG(t-1)$ and store them in local macros. We also create interaction terms between the G-lagged variable and $SG(t)$ variables. These SG variables are the year-on-year percentage change of real per capita investment in provinces which belong to the same region as i, as a ratio of lagged real per capita value added. Finally, we conduct a regression analysis for each variable list, where we regress the variables on the year and ID variables, but only include observations from 1990 to 1999. We save the residuals of this regression and replace them with the residuals of the full sample. Additionally, we label certain variables such as $Province$, $Region$, $Year$, $Group$, etc.

A.4 Making the Baseline

To obtain our results, we have to do several steps. Firstly, we create a list of control variables which contain the variables $Mafiosi, Extortion, Corruption1, Corruption2, Murder$ and some lagged variables. Next, we perform linear regression analyses using two models - one with lagged values of Y included and one without. After running the regressions, we test the joint significance of the instrument in the second model. We observe that CD_1S and $L1CD\_S2$ are jointly significant, with an F-statistic of 12.58 and a p-value of 0.0000. Finally, we estimate Instrumental Variable (IV) regression models, where the first two models include only G, CD_s1, and $L1CD\_S2$ as independent variables. The last two models additionally include lagged values of Y.

The results of the first-stage regression of G are presented in Table 7. After doing tests on

Table 7: First-stage regression of G

G	Coefficient	Robust std. err.	t	P >‖t‖
CD_S1	-2.067	0.537	-3.85	0.000
L1CD_S2	-4.022	0.983	-4.09	0.000
L1G	-0.413	0.065	-6.32	0.000
L2G	-0.126	0.056	-2.21	0.028

Notes: CD_S1 refers to the number of municipalities that have been placed under the administration of external commissioners by the central government due to their ties with the Mafia, provided that the official decree is published in the first half of the year. $L1CD\_S2$ is the lagged version of CD_S2, which is similar to CD_S1 but takes into account cases where the average number of days between the dismissal of the city council and the end of the year is less than 180. Additionally, the regression model includes one-period and two-period lagged versions of G, representing the year-on-year percentage change of real per-capita public investment in infrastructure (adjusted to 1995 prices) relative to lagged real per-capita value-added.

the results for these first-stage estimations we find that the first-stage test statistics are cluster robust, that the model is not under-identified and that the estimation equation is also not weakly identified. Finally, from the Anderson-Rubin Wald test we find that the endogenous regressors are jointly significant and that the orthogonality condition holds.

Following that, the results of the 2-stage least square estimation can be found in Table 8

Table 8: 2SLS estimation results

Y	Coefficient	Robust std. err.	z	P >‖z‖
G	1.457	0.492	2.96	0.003
L1G	0.726	0.206	3.52	0.000
L2G	0.141	0.107	1.32	0.186

Notes: This table presents G, along with its lagged versions (one and two periods). G represents the year-on-year percentage change of real (1995 price) per-capita public investment in infrastructure, expressed as a ratio of lagged real per-capita value-added. Y is the percentage growth rate of real per-capita total value added.

Based on our statistical tests, we can conclude that the model is adequately identified and there is no issue of weak identification. Furthermore, after performing the Hansen-J-test, we also determine that there is no overestimation.

Next, the first-stage regression results including lagged output Y can be found in Table 9. The estimation analysis indicates that the model is still identified, and the endogenous regressions remain jointly significant. Moreover, the orthogonality conditions remain valid.

Table 9: First-stage regression of G including lagged Y

G	Coefficient	Robust std. err.	t	P >‖t‖
CD_s1	-1.973	0.562	-3.51	0.000
L1CD_s2	-4.076	9.363	-4..35	0.000
L1G	-0.414	0.065	-6.35	0.000
L2G	-0.129	0.059	-2.18	0.029
L1Y	0.029	0.020	1.44	0.152
L2Y	-0.015	0.017	-0.90	0.488

Notes: The variables used in this table, similar to those in Table 7, now incorporate lagged versions of Y. Y represents the percentage growth rate of real per-capita total value added.

The outcomes of the 2-stage least squares estimation, including lagged variables of Y, are presented in Table 10, which demonstrates that the model is accurately identified, just as before.

Table 10: 2-Stage Least Squares estimation results of G including lagged Y

G	Coefficient	Robust std. err.	z	P >‖z‖
G	1.552	0.428	3.62	0.000
L1G	0.793	0.190	4.18	0.000
L2G	0.193	0.108	1.79	0.073
L1Y	-0.198	0.064	-3.08	0.002
L2Y	-0.020	0.054	-0.37	0.708

Notes: Similar to previous results, this table presents the variables G and Y, along with their corresponding lagged values.

Table 11 presents a summary of all six regression models. The first two columns show the OLS estimates, with coefficients and significance that match those obtained by Acconcia et al. (2014). The estimated impact multiplier remains at 0.2. The last four columns show the results of the IV estimation models, which were conducted with and without lagged values of Y. The third and fifth columns present the results of the first-stage regressions, which indicate that provinces under council dismissals experience significant drops in public investment, as evidenced by the negatively significant coefficients of G. The power of the two instruments is 12.58 and 11.83, respectively, which is the same as in Acconcia et al. (2014). In the second-stage regression, we observe that the point estimate for contemporaneous spending (excluding lagged output) is 1.46, while the overall point estimate is 1.55. This suggests that a 1 percent reduction in local public infrastructure, relative to local value-added, leads to a contemporaneous spending reduction of 1.5 percent. Importantly, the coefficient for contemporaneous spending is significantly different from zero in both versions of the model. This discrepancy between the OLS and IV estimates of contemporaneous spending is consistent with the findings of Acconcia et al. (2014), indicating a downward bias in the OLS estimates. Assuming exogeneity of lagged spending with respect to current output, the overall point estimate, including lagged Y values, is determined to be 1.93. This estimate is derived by summing the contemporaneous spending variable $G(t)$ with its one-period lagged value and taking into account the influence of the first lag of the dependent variable in the first stage.

Table 11: Public spending multiplier for G and Y

	OLS	OLS (including lagged Y)	First stage	Second stage	First stage (including lagged Y)	Second stage (including lagged Y)
G(t)	0.21**	0.23**		1.46**		1.55***
	(0.07)	(0.07)		(0.49)		(0.43)
G(t-1)	0.22**	0.26**	-0.41***	0.73***	-0.41***	0.79***
	(0.08)	(0.08)	(0.07)	(0.21)	(0.07)	(0.19)
G(t-2)	0.00	0.04	-0.13*	0.14	-0.13*	0.19
	(0.07)	(0.07)	(0.06)	(0.11)	(0.06)	(0.11)
Y(t-1)		-0.16*			0.03	-0.20**
		(0.06)			(0.02)	(0.06)
Y(t-2)		-0.03			-0.02	-0.02
		(0.05)			(0.02)	(0.05)
Ftest_instruments			12.58		11.83	

Notes: Data is collected on an annual basis from 1990 to 1999. $G(t)$ represents the year-on-year change in per capita real infrastructure investment divided by the previous year's per capita real value added. Lagged values of G, namely $G(t-1)$ and $G(t-2)$, are included as one-period and two-period lags, respectively. Y represents the percentage growth rate of real per-capita total value added. The robust standard errors are reported in the brackets. The significance is denoted as follows:
* Significant at the 5 percent level.
** Significant at the 1 percent level.
*** Significant at the 0.1 percent level.

A.5 Checking Exclusion Restriction

To investigate whether the exclusion restriction is valid and to determine if Mafia activities during council dismissals have an impact on output beyond variations in public spending, we perform an analysis to examine how our estimates of the spending multiplier change when we omit controls from the regression model. The aim is to determine the net effect of reducing Mafia activity on spending output. If removing controls for police investigation leads to an increase in the multiplier, then we can infer that changes in Mafia activities following a city council dismissal can result in output losses.

To obtain these results, we begin by estimating an IV regression for the variable Y, using G as our endogenous regressor, and CD_s1 and $L1CD\_s2$ as our instruments. Additionally, we include several control variables and interact $L2CD$, $L3CD$, $L1U1$, $L1U2$, $L2U1$, and $L2U2$ with the instruments. We conduct these IV regressions for Y for each of the local macros "Resignation", "Election", "Budget", and "Others." Finally, we summarise our findings in Table 12.

Table 12: Exclusion restriction estimation

	(1)	(2)	(3)	(4)	(5)
G(t)	1.30**	1.56***	1.53***	1.59***	1.64***
	(0.45)	(0.41)	(0.44)	(0.47)	(0.44)
G(t-1)	0.69***	0.79***	0.78***	0.81***	0.82***
	(0.19)	(0.19)	(0.19)	(0.20)	(0.20)
G(t-2)	0.16	0.19	0.19	0.20	0.20
	(0.09)	(0.11)	(0.11)	(0.11)	(0.11)
Y(t-1)	-0.19**	-0.20**	-0.20**	-0.20**	-0.20**
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Y(t-2)	-0.02	-0.01	-0.02	-0.02	-0.01
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Resignation(t)		-0.00			
		(0.05)			
Resignation(t-1)		0.04			
		(0.06)			
Election(t)			-0.03		
			(0.08)		
Election(t-1)			0.03		
			(0.13)		
Budget-no confidence				0.03	
				(0.15)	
Budget-no confidence(t-1)				-0.16	
				(0.16)	
Others(t)					0.45
					(0.39)
Others(t-1)					0.29
					(0.39)
Ftest_instruments	12.56	14.17	12.30	12.12	14.75

Notes: In column 1, the results are presented after eliminating proxies for Mafia activity, allowing for a focused examination of other variables. Columns 2 to 5 offer an exploration of the subject by incorporating additional controls to account for council dismissals unrelated to Mafia infiltration. The control variable *Budget-no confidence* considers instances where the council fails to pass the annual budget, as well as political crises that impede its normal functioning. Furthermore, the control variable *Others* encompasses all other possible circumstances leading to council dismissals that are unrelated to the Mafia.
The robust standard errors are reported in the brackets. The significance is denoted as follows:
* Significant at the 5 percent level.
** Significant at the 1 percent level.
*** Significant at the 0.1 percent level.

This table presents the results of different regression models that examine the effect of controls for Mafia activity on the spending multiplier. The first column excludes the proxies for Mafia activity, while columns 2 to 5 add controls for council dismissals that are not related to Mafia infiltration. The coefficient for the spending contraction in column 1 is less negative, indicating a fall in the spending multiplier when we exclude controls for Mafia activity. This suggests that police investigations against the Mafia have an overall positive short-run output effect. In columns 2 to 5, the estimated coefficients for dismissals of city councils due to reasons unrelated to Mafia infiltration are not significant, indicating that they do not have an effect on output. In their study, Acconcia et al. (2014) examined here the impact of changes in Mafia presence during a council dismissal on public spending as a necessary exclusion restriction. Their findings suggested that the Mafia's presence may have a dampening effect on economic activity during council dismissals. In our research, we aim to investigate the causal relationship between Mafia presence and public spending, focusing on whether a reduction in Mafia presence is associated with decreased public spending in general. By broadening the analysis beyond immediate council dismissals, our study seeks to deepen our understanding of the dynamics between Mafia presence and public spending.

A.6 Spillovers/Cross-border Effects

Spending variations could also have some effects on the economic activity in nearby provinces. To investigate this spillover or cross-border effects we carry out an analysis by extending the used set of regressors and by aggregating small clusters of provinces. The results can be found in Table 13.

Table 13: Spillover effects

	(1)	(2)	(3)
G(t)	1.44**	1.50***	1.24**
	(0.47)	(0.041)	(0.45)
G(t-1)	0.73***	0.76***	0.74**
	(0.20)	(0.17)	(0.23)
G(t-2)	0.17	0.20	0.17
	(0.11)	(0.10)	(0.16)
Y(t-1)	-0.20**	-0.20**	-0.21**
	(0.06)	(0.06)	(0.08)
Y(t-2)	-0.02	-0.02	-0.05
	(0.05)	(0.05)	(0.06)
SG(t)	0.20		
	(0.18)		
SG(t-1)	0.35*		
	(0.16)		
G(t-1) x SG(t-1)		0.19	
		(0.12)	
Ftest_instruments	10.61	12.00	24.20

Notes: In the first column, the variable SG represents public spending in provinces within the same region as province i, excluding province i itself. The second column introduces an interaction term between $SG(t-1)$ and $G(t-1)$, where both variables are measured as deviations from their mean values. This interaction term captures the combined influence of public spending in neighbouring provinces and the lagged year-on-year change in per capita real infrastructure investment. Moving to the third column, the original observations are replaced with aggregated data from multiple provinces. This aggregation allows for a broader perspective by considering the collective impact of the variables across provinces. The robust standard errors are reported in the brackets. The significance is denoted as follows:
* Significant at the 5 percent level.
** Significant at the 1 percent level.
*** Significant at the 0.1 percent level.

Column 1 of the table includes the variable $SG_{i,t}$ and its first lag, which measures the year-on-year percentage change of real per capita investment in provinces belonging to the same region as i, as a ratio of lagged real per capita value added. The coefficients of these variables are low, and the coefficient for $SG_{i,t}$ is insignificant. Column 2 adds an interaction term between $SG_{i,t}$ and the year-on-year percentage change of real per capita investment as a ratio of lagged real per capita value added (G), but this term is also insignificant. The inclusion of the spillover term has little effect on the point estimates of the coefficients on the contemporaneous and lagged spending variables. Finally, column 3 replaces small provinces with aggregated ones, resulting in similar coefficients but a slightly better fitting model based on the increased F-stat.

A.7 Dropping Provinces

We aimed to determine if specific provinces had an oversised influence on our findings, potentially biasing the results. To assess this, we examined if our results still held when excluding certain provinces. Table 14 displays the findings after removing the seven provinces with the highest number of council dismissals: Napoli, Caserta, Palermo, Catania, Salerno, Bari, Reggio, and Calabria. Notably, the coefficients for G(t) remain statistically significant at the 5 percent level, and the coefficients for the first lag of public spending also maintain their significance at the 5 percent level, following similar patterns. These outcomes imply that our model is not overly sensitive to particular provinces.

Table 14: Provincial bias check

	NA	CE	PA	CT	SA	BA	RC
G(t)	1.86***	1.47**	1.46**	1.35*	1.36**	1.53**	1.37**
	(0.44)	(0.47)	(0.46)	(0.54)	(0.47)	(0.41)	(0.43)
G(t-1)	0.93***	0.76***	0.76***	0.72**	0.72***	0.78***	0.73***
	(0.22)	(0.21)	(0.20)	(0.24)	(0.21)	(0.19)	(0.18)
G(t-2)	0.24	0.17	0.18	0.16	0.18	0.18	0.16
	(0.12)	(0.11)	(0.11)	(0.11)	(0.10)	(0.11)	(0.10)
Y(t-1)	-0.20**	-0.21**	-0.20**	-0.20**	-0.19**	-0.19**	-0.17**
	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Y(t-2)	-0.00	-0.03	-0.02	-0.03	-0.02	-0.01	-0.04
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Ftest_instruments	19.59	9.48	11.31	10.90	9.25	11.85	9.42

Notes: The table presents estimates obtained by excluding specific important cities in each column. The cities are represented by abbreviations such as NA for Naples, CE for Caserta, PA for Palermo, CT for Catania, SA for Salerno, BA for Bari, and RC for Reggio Calabria. Each column allows for a focused analysis of the estimates and their variations when a particular city is excluded from the model. The robust standard errors are reported in the brackets. The significance is denoted as follows:
* Significant at the 5 percent level.
** Significant at the 1 percent level.
*** Significant at the 0.1 percent level.

A.8 Further Results

The first column of Table 15 explores the effect of restricting the sample to southern provinces to test for heterogeneity across macro areas. The contemporaneous and lagged spending coefficients increase slightly, while the lagged output growth becomes even more negative, suggesting that the multiplier is not affected by macro area differences.

In the second column, the year-fixed effect is removed to test for the influence of national monetary policies and cyclical fluctuations. The contemporaneous spending coefficient increases again, while the lagged spending and output coefficients remain relatively unchanged.

Finally, in the third column, province-fixed effects are excluded to test for spurious cross-sectional effects. The point estimate increases to 1.62, but the remaining coefficients are not affected. Overall, these sample restrictions do not significantly alter the baseline estimation.

Table 15: Further Results

	South	Drop lambda	Drop alpha
G(t)	1.89***	1.92***	1.62***
	(0.42)	(0.52)	(0.37)
G(t-1)	0.95***	0.75***	0.74**
	(0.19)	(0.27)	(0.18)
G(t-2)	0.23	0.12	0.12
	(0.14)	(0.13)	(0.10)
Y(t-1)	-0.34***	-0.14*	-0.11
	(0.10)	(0.06)	(0.07)
Y(t-2)	-0.01	0.09	0.05
	(0.08)	(0.07)	(0.06)
F-stat instruments	10.54	23.89	13.16
Observations	340	950	950

Notes: In column 1, we focus on southern Italy, analysing its specific regions. In column 2, we exclude year dummies to solely examine variable relationships. In the third column, province dummies are dropped, disregarding province-specific effects. The robust standard errors are reported in the brackets. The significance is denoted as follows:
* Significant at the 5 percent level.
** Significant at the 1 percent level.
*** Significant at the 0.1 percent level.

B Appendix B: Summary Statistics

Table 16: Summary statistics of every region

Period	G			Population			U1			U2			Murder		
	Overall	Post	Pre	Overall	Post	Pre	Overall	Post	Pre	Overall	Post	Pre	Overall	Post	Pre
Sicilia	-0.390	-0.174	-0.607	557845.8	563837.7	551853.9	-0.068	-0.080	-0.056	-0.009	-0.195	-0.002	0.001	-0.001	0.004
Calabria	-0.196	0.010	-0.403	691648.9	690277.8	693020.1	-0.067	-0.099	-0.036	-0.008	-0.024	0.009	0.001	-0.002	-0.001
Campania	-0.376	-0.092	-0.659	1136150	1151041	1121259	-0.093	-0.151	-0.034	-0.010	0.003	-0.006	-0.004	0.000	-0.007
Puglia	-0.090	-0.033	-0.148	808969.6	815593.9	802345.4	-0.033	-0.108	-0.042	-0.008	-0.017	0.001	0.000	0.000	0.001
Abruzzo	-0.070	-0.099	-0.042	314117.4	317588.5	310646.2	-0.085	-0.098	-0.072	-0.085	-0.016	0.005	0.000	0.000	0.000
Basilicata	-0.153	0.366	-0.672	305010.2	304633.6	305386.7	-0.085	-0.155	-0.015	-0.010	-0.015	-0.005	0.000	0.000	0.000
Emilia Romagna	0.023	0.021	0.025	490220.5	492477.7	487963.3	-0.181	-0.147	-0.216	0.003	-0.006	0.012	0.000	0.000	0.000
Friuli Venezia Giulia	-0.228	-0.070	-0.386	298630.5	297137.6	300123.4	-0.147	-0.180	-0.114	0.007	-0.002	0.016	0.000	0.000	0.000
Lazio	0.038	-0.179	-0.104	1033069	1043043	1023096	-0.078	-0.088	-0.067	-0.000	-0.018	0.016	0.000	0.000	0.000
Liguria	0.146	0.235	0.057	418242.6	412647.8	423837.3	-0.075	-0.099	-0.051	-0.002	-0.012	0.008	0.000	0.000	0.000
Lombardia	-0.022	0.017	-0.062	988585.4	995287.9	981882.9	-0.089	-0.126	-0.052	0.003	-0.007	0.012	0.000	0.000	0.000
Marche	-0.165	-0.063	-0.267	358690.3	361604.5	355776	-0.164	-0.145	-0.183	-0.008	-0.010	-0.006	0.000	0.000	0.000
Molise	-0.721	0.039	-1.482	165237	165290.1	165183.8	-0.081	-0.016	-0.145	-0.014	-0.014	-0.015	0.000	0.000	0.000
Piemonte	-0.041	0.010	-0.092	632133.3	630537.9	633728.6	-0.106	-0.147	-0.065	0.000	-0.009	0.009	0.000	0.000	0.000
Sardegna	0.137	-0.394	0.668	412039	414380.8	409697.2	-0.082	-0.056	-0.108	0.003	-0.017	0.022	0.000	0.000	0.000
Toscana	-0.021	0.101	-0.143	392325.3	391988.3	392662.4	-0.136	-0.151	-0.121	0.001	-0.007	0.008	0.000	0.000	0.000
Trentino Alto Adige	-0.021	-0.069	0.026	450099.7	458187.2	442012.2	-0.071	-0.084	-0.058	0.008	-0.002	0.018	0.000	0.000	0.000
Umbria	0.105	0.080	0.131	409056.6	413259.4	404853.9	-0.118	-0.191	-0.046	-0.004	-0.015	0.006	0.000	0.000	0.000
Veneto	-0.043	0.041	-0.128	629578.6	635484.8	623672.4	-0.138	-0.163	-0.113	0.003	-0.004	0.011	0.000	0.000	0.000

Notes: This table displays the average values of various variables for all the states in Italy, both before and after a specific event. It includes the overall average as well. The variable G represents the year-on-year percentage change of real per-capita public investment in infrastructure, measured relative to the lagged real per-capita value added. The variables $U1$ and $U2$ indicate the changes in the natural logarithm of per capita employment and per capita hours of wage supplement provided by the unemployment insurance scheme, respectively. Lastly, the variable $Murder$ represents the difference in the number of people reported by the police to the judicial authority due to murder cases associated with Mafia-related activities.

Table 17: Summary statistics every region (part 2)

Period	CD			Extortion			Corruption1			Corruption2			Mafiosi		
	Overall	Post	Pre	Overall	Post	Pre	Overall	Post	Pre	Overall	Post	Pre	Overall	Post	Pre
Sicilia	0.019	0.033	0.004	0.006	0.007	0.005	-0.002	0.005	-0.009	0.002	0.003	0.000	0.023	0.011	0.036
Calabria	0.019	0.009	0.029	0.006	0.009	0.003	0.002	-0.001	0.005	0.002	0.002	0.003	0.020	0.041	-0.001
Campania	0.035	0.058	0.013	0.002	0.003	0.001	-0.002	0.002	-0.006	0.002	0.002	0.001	0.004	0.001	-0.009
Puglia	0.007	0.010	0.003	0.008	-0.004	0.020	0.000	0.004	-0.004	0.000	0.001	0.000	0.003	0.005	0.002
Abruzzo	0	0	0	0.004	-0.001	0.009	-0.003	0.003	-0.009	0.001	0.002	0.001	0.000	0.011	0.000
Basilicata	0.001	0.003	0	0.007	0.014	0.001	0.002	0.006	-0.001	0.002	0.003	0.002	0.015	-0.021	0.050
Emilia Romagna	0	0	0	0.002	0.003	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.000	0.000	0.001
Friuli Venezia Giulia	0	0	0	-0.000	0.004	-0.004	0.000	0.002	-0.002	0.001	0.002	-0.001	0.000	0.000	0.000
Lazio	0	0	0	0.001	0.005	-0.003	0.001	-0.001	0.002	0.001	0.001	0.000	0.000	-0.001	0.001
Liguria	0	0	0	0.003	0.004	0.002	0.001	-0.002	0.004	0.002	0.000	0.004	0.001	-0.001	0.004
Lombardia	0	0	0	0.002	0.001	0.002	-0.001	-0.000	-0.001	-0.001	-0.004	0.001	-0.001	0.000	-0.001
Marche	0	0	0	0.002	0.005	-0.001	0.000	-0.001	0.001	-0.000	0.000	-0.001	0.000	0.001	-0.001
Molise	0	0	0	-0.000	-0.000	-0.001	0.007	0.011	0.003	0.008	0.005	0.010	0.001	0.001	0.000
Piemonte	0.000	0.000	0	0.000	0.000	-0.002	-0.001	0.001	-0.003	0.000	-0.000	0.001	0.000	0.002	-0.001
Sardegna	0	0	0	0.007	0.006	0.009	-0.001	0.000	-0.003	0.000	-0.001	0.002	0.003	0.005	0.000
Toscana	0	0	0	0.002	0.005	-0.000	-0.003	0.002	-0.007	0.001	0.001	0.001	0.001	-0.002	0.005
Trentino Alto Adige	0	0	0	0.004	0.004	0.003	0.002	0.006	-0.001	0.002	0.003	0.001	0.000	0.000	0.000
Umbria	0	0	0	0.002	0.005	-0.002	-0.000	0.000	-0.001	0.001	0.001	0.001	0.000	0.000	0.000
Veneto	0	0	0	0.001	0.001	0.002	-0.003	-0.001	-0.005	0.000	-0.003	0.004	-0.001	0.000	-0.001

Notes: The table shows average values for different control variables before and after an event. *CD* represents the number of municipalities under external commissioners due to ties with the Mafia. A value of 0 distinguishes no dismissals from very low numbers. Extortion tracks changes in reported cases of extortion. Corruption1 reflects changes in the number of people reported to the judicial authority because of corruption. Corruption2 measures changes in reported corruption-related crimes. Mafiosi monitors the changes in reported cases associated with the Mafia.

C Appendix C: Predictor Variable Balance

Table 18: Predictor Variable Balance

	Actual treatment group	Synthetic Control group
G(t-1)	-0.011	-0.020
G(t-2)	-0.058	-0.027
Y(t)	3.269	2.186
Y(t-1)	1.791	1.792
Y(t-2)	0.566	0.668
CD(t)	-0.023	-0.009
CD(t-2)	-0.021	0.008
CD_S1(t)	-0.015	-0.005
CD_S2(t)	0.015	0
CD_S2(t-1)	-0.012	0.004
Corruption_1(t)	-0.012	-0.011
Corruption_1(t-1)	-0.012	-0.004
Corruption_1(t-2)	-0.001	-0.016
Corruption_2(t)	-0.010	-0.012
Corruption_2(t-1)	-0.005	-0.005
Corruption_2(t-2)	0.002	-0.009
Extortion(t)	0.008	0.000
Extortion(t-1)	-0.016	-0.018
Extortion(t-2)	0.002	-0.007
Mafiosi(t)	-0.014	-0.017
Mafiosi(t-1)	-0.014	-0.001
Mafiosi(t-2)	0.021	-0.007
Murder(t)	0.000	0.000
Murder(t-1)	-0.003	0.000
Murder(t-2)	-0.001	0.000
U1(t)	0.056	0.021
U1(t-1)	0.096	0.088
U1(t-2)	0.030	0.011
U2(t)	0.010	0.003
U2(t-1)	0.010	-0.004
U2(t-2)	0.004	-0.003

Notes: This table shows the predictor variable balance between the actual treatment group and the Synthetic Control group. We see that the differences are minimal which suggests that the Synthetic Control group can be used as a counterfactual control group.

D Appendix D: VIF Tables

Table 19: VIF table for DiD regression including lagged G and Y

	VIF	1/VIF
Treatment	5.14	0.195
Post-event	1.35	0.743
Treatment x post-event	5.51	0.182
G(t-1)	1.25	0.798
G(t-2)	1.27	0.787
Y(t)	1.13	0.884
Y(t-1)	1.12	0.896
Y(t-2)	1.06	0.940
CD(t)	7.62	0.131
CD(t-2)	1.40	0.716
CD_S1(t)	3.38	0.296
CD_S2(t)	5.17	0.193
CD_S2(t-1)	2.08	0.480
Corruption_1(t)	1.54	0.650
Corruption_1(t-1)	2.00	0.501
Corruption_1(t-2)	1.52	0.658
Corruption_2(t)	1.40	0.715
Corruption_2(t-1)	1.81	0.554
Corruption_2(t-2)	1.49	0.672
Extortion(t)	1.61	0.622
Extortion(t-1)	1.95	0.514
Extortion(t-2)	1.60	0.626
Mafiosi(t)	1.34	0.744
Mafiosi(t-1)	1.32	0.755
Mafiosi(t-2)	1.23	0.815
Murder(t)	1.81	0.553
Murder(t-1)	3.08	0.324
Murder(t-2)	1.85	0.541
U1(t)	1.33	0.751
U1(t-1)	1.43	0.701
U1(t-2)	1.25	0.797
U2(t)	1.15	0.866
U2(t-1)	1.13	0.884
U2(t-2)	1.16	0.864
Mean VIF	2.07	

Table 20: VIF table for Synthetic Control regression including lagged G and Y

	VIF	1/VIF
Treatment_post_event	2.37	0.422
Synthetic_post_event	3.01	0.333
G(t-1)	7.34	0.136
G(t-2)	4.98	0.201
Y(t)	4.03	0.248
Y(t-1)	3.33	0.300
Y(t-2)	3.00	0.333
CD(t)	13.39	0.075
CD(t-2)	3.00	0.334
CD_S1(t)	10.45	0.096
CD_S2(t)	3.93	0.254
CD_S2(t-1)	4.25	0.235
Corruption_1(t)	9.35	0.107
Corruption_1(t-1)	11.51	0.087
Corruption_1(t-2)	8.77	0.114
Corruption_2(t)	8.80	0.114
Corruption_2(t-1)	11.11	0.090
Corruption_2(t-2)	7.25	0.138
Extortion(t)	7.12	0.140
Extortion(t-1)	7.98	0.125
Extortion(t-2)	4.27	0.234
Mafiosi(t)	3.72	0.269
Mafiosi(t-1)	5.14	0.195
Mafiosi(t-2)	3.72	0.269
Murder(t)	4.30	0.232
Murder(t-1)	6.93	0.144
Murder(t-2)	3.92	0.255
U1(t)	3.41	0.294
U1(t-1)	2.73	0.367
U1(t-2)	4.79	0.209
U2(t)	2.52	0.397
U2(t-1)	3.22	0.311
U2(t-2)	3.28	0.305
Mean VIF	5.66	

Notes: Given that $Corruption1$ and $Corruption2$ are highly correlated with each other, it is anticipated that their VIF scores are elevated. This is because both variables essentially capture the same underlying concept. The same reasoning can be applied to the CD variables. Consequently, although these specific variables exhibit high VIF scores, it is justifiable to disregard these scores due to the logical explanation behind them.

E Programming Code

We begin our analysis by replicating the study conducted by Acconcia et al. (2014), using the replication package provided with their article. The replication allows us to thoroughly understand their findings and identify any potential limitations or inconsistencies. Following the replication, we proceed with a data summary, examining the means of the variables before and after the event. To accomplish this, we filter the observations using the "by(region)" and "by(period)" commands.

Next, we move on to conducting the Difference-in-Differences (DiD) estimation. We generate regressors based on the approach outlined by Acconcia et al. (2014) and perform a Chow-break test to assess the validity of the parallel assumption. To do this, we manually calculate the residuals for the full sample, pre-event sample, and post-event sample. Using these residuals, along with the number of regressors (k) and the number of observations (N), we calculate the Residual Sum of Squares (RSS) and generate the Chow statistic. Once we confirm that the parallel assumption holds, we create a treatment variable that includes all observations from the regions in the treatment group. This variable acts as an indicator, taking the value of 1 or 0. We define pre-event and post-event indicators and proceed with several DiD regressions. Additionally, we conduct a Variance Inflation Factor (VIF) test using the "vif" command. To ensure a balance between the treatment and control group covariates, we perform t-tests for all variables and utilise the "by(treatment)" command. Finally, we conduct a serial correlation test using the "xtserial" command, which requires the full regression used in the DiD estimation. We repeat this entire process for different estimations that include various additional regressors.

To apply the Synthetic Control Method, we first install the synth package by executing the command "ssc install synth, replace all". Next, we construct our Synthetic control dataset. Since the "synth" command can only handle one set of treatment group observations for generating weights, we cannot include all four of our regions individually. Therefore, we took the average of the four regions and compress them into a single region with 11 years of observations. This same compressing process was applied to the potential control units as well, as the original dataset contains multiple provinces within each region. By compressing the observations from each province within the regions and taking the average of them, we obtain three compressed Synthetic Control regions and one treatment group. We then employ the "synth" command to evaluate the statistical usability of the desired regression. This command includes all control variables and the dependent variable G. Additionally, we add $trunit(1)$ to specify that the treatment unit has the ID number 1 and use $counit(234)$ to indicate the three different control units with ID numbers 2, 3, and 4 respectively. The treatment period is set to start in 1992 with $trperiod(1992)$, and the results are generated for the period covering 1988 to 1998 using the $resultsperiod(1988(1)1998)$ command. We include *nested* and *allopt* to perform the necessary nested optimisation for the three different ways to describe the V-matrix. From the "synth" command, we obtain balance statistics and the root mean squared error (RMSE) to assess the reasonableness of our Synthetic Control units for analysis. Finally, we extract the weights for the three different Synthetic Control regions.

Similar to the DiD approach, we generate the regressors based on the methodology presented by Acconcia et al. (2014). We then proceed with conducting the Synthetic Control estimations.

Initially, we define the treatment and potential Synthetic Control units by selecting the regions we want to include in each group. Subsequently, we create a treatment group indicator that takes the value of 1 if the region belongs to the treatment group. We create pre-event and post-event indicators and use the constructed weight to create the G_Synth variable, which represents the G variable for the Synthetic Control group. Additionally, we generate two different G_diff variables, $G\_diff\_treated$ and G_diff_synth, and combine them into a single G_diff variable. We utilise this newly created variable to conduct the estimation, which follows a baseline form similar to the DiD approach but now used the indicator variables $treatment\_post\_event$ and the $synth\_control\_post\_event$. Similar to DiD estimations, we conduct VIF and balance tests, as well as serial correlation and placebo tests based on the Mean Squared Prediction Error. Finally, we repeat this entire process of using different robustness checks for all iterations of the Synthetic Control estimations.