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KEYWORDS

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Fiscal Policy Divergence*

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Abstract

We propose a novel measure of fiscal policy divergence based on public budget data. First, we quantify policy similarity across municipalities based on the cosine similarity of their budget allocations, showing strong correlations with geographic proximity and socio-demographic characteristics similarity. Next, we predict budget similarity out-of-sample using similarities in population composition, defining policy divergence as the deviation between observed and predicted similarities. In an empirical application to 8,000 Italian municipalities (2000–2015), we show that divergence significantly decreases in election years, suggesting politicians strategically set the more expected policies in the lead-up to elections.

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1. Introduction

Fiscal policy is a crucial tool for local governments, shaping their capacity to deliver essential services and promote economic growth within their jurisdictions. Ideally, the allocation of expenditure and generation of revenue should be structured to address local needs while prioritizing public welfare (Oates, 1972). Indeed, if local preferences and demographics significantly influence the optimal policy choices (Agrawal, Hoyt and Wilson, 2022), fiscal policy should mirror the specific characteristics of the local community. However, evaluating how well a fiscal policy is consistent with the local population's needs can be challenging without a benchmark or standard for comparison.

In this paper, we propose a novel approach that involves a comparative analysis of government performance across jurisdictions with similar socio-demographic compositions. We aim to assess how accurately the budget allocation of a specific jurisdiction can be predicted from its characteristics and to compare it with the budget allocations of other jurisdictions with similar socio-demographic profiles. The standard public finance literature frequently emphasizes the role of neighboring jurisdictions' policies as accessible and informative benchmarks for voters to hold politicians accountable (Besley and Case, 1995). Our intuition builds upon this argument, but rather than using geographic proximity as a stand-in for similarity across jurisdictions, we explicitly consider the proximity of socio-demographic factors. Next, we argue that any significant deviation between the actual and predicted allocations could serve as a good proxy for a local government's unexpected action. We remain agnostic about the source or normative meaning of such divergence: for instance, it may capture innovative policymaking (Bernecker, Boyer and Gathmann, 2021), but it could equally reflect inefficiencies, mismanagement, or corruption (Bandiera, Prat and Valletti, 2009). Our contribution is to provide a consistent way to detect and quantify these departures, leaving their interpretation to the context of specific applications.

To demonstrate our approach, we draw on detailed data on public budgets and socio-demographic characteristics for roughly 8,000 Italian municipalities between 2000 and 2015. Municipal budgets provide a reliable proxy for government policy, as they reflect choices over spending, revenue, and resource allocation. Our first contribution is to construct a comprehensive measure of budget similarity across municipalities by analyzing the entire structure of local budgets with tools from applied machine learning. We represent each municipality's budget as a high-dimensional vector—spanning approximately

4,500 categories—and compute similarity as the cosine of the angle between these vectors. A higher cosine similarity indicates that two municipalities allocate resources in more comparable ways, capturing the closeness of their budgetary choices. Importantly, we show that municipalities that are geographically proximate, share similar population structures, or are led by mayors from the same political party exhibit markedly higher budget similarity. Among these factors, geographic distance and population age composition stand out as the strongest predictors. By contrast, individual attributes of mayors—such as age or gender—have little explanatory power, suggesting that local fiscal choices are shaped more by structural and political contexts than by personal characteristics of officeholders.

We next assess how actual budgets diverge from those predicted by municipalities' socio-demographic characteristics. The guiding principle is straightforward: jurisdictions with similar socio-demographic composition should display similar fiscal choices. Deviations from these expected patterns, therefore, capture what we refer to as fiscal divergence. To quantify this, we estimate a fixed-effects regression separately by region and year, predicting the cosine similarity of budget allocations between municipality pairs using the cosine similarity of a rich set of socio-demographic characteristics, while controlling for municipality-specific fixed effects. This approach isolates the role of demographic similarity in shaping budget similarity and absorbs unobserved, time-invariant municipal traits. We evaluate predictive performance using 5-fold cross-validation, repeatedly training the model on subsets of the data and testing out-of-sample. On average, the model attains an R-squared of 0.536, with predicted rankings of municipal similarity closely tracking observed rankings—evidence that our predictions are both accurate and reliable.

The residuals from these predictions—capturing the gap between observed and expected budget similarity—provide a measure of how much a municipality's fiscal choices diverge from those of its comparable peers. Larger residuals indicate greater divergence, signaling instances where budget allocations depart more strongly from demography-based expectations.

To provide a practical example of how our measure can be applied, we study the role of electoral incentives in shaping local fiscal choices through the political budget cycle. Specifically, we test whether fiscal divergence from demography-based expectations varies systematically over the electoral cycle, exploiting the staggered timing of municipal elections across Italian municipalities (Repetto, 2018; Ferraresi, 2020). We find that divergence declines in the year preceding elections. This pattern is consistent with Bernecker, Boyer and Gathmann (2021), who show that incumbents facing re-election avoid risky departures, and with Drazen and Eslava (2010), who emphasize that politicians adjust the composition of spending to signal responsiveness to voter priorities.

We complement the body of literature examining fiscal policy and its driving factors. The determinants of fiscal policy include the characteristics of the mayor and the ruling party (Ferreira and Gyourko, 2014; Brollo and Troiano, 2016); media exposure, such as the influence of conservative or progressive media channels on voters' preferences, which can be reflected in diverging budget allocation choices made by newly elected politicians (Ash and Galletta, 2023); the degree of decentralization or fiscal autonomy enjoyed by local policymakers (Daniele and Giommoni, 2025; Grembi, Nannicini and Troiano, 2016); electoral rules and term limits (Gagliarducci and Nannicini, 2013); and monetary incentives (Ferraz and Finan, 2009). Unlike previous studies that typically focus on a specific component of local policymaking, our method accounts for the overall composition of the budget, thereby improving the analysis of fiscal decisions.

Additionally, we contribute to the growing literature in economics that employs methodologies from machine learning to overcome data limitations and generate new variables for further analysis. Examples include the use of text-as-data to provide evidence of increasing polarization in US politics (Gentzkow, Shapiro and Taddy, 2019) and biased decision-making (Ash, Chen and Galletta, 2022; Ash, Chen and Ornaghi, 2024; Krieger, Myers and Stern, 2023; Bello, Casarico and Nozza, 2023), or the application of LDA topic modeling to characterize CEO behavior (Bandiera et al., 2020) and voters' ideology (Draca and Schwarz, 2024). Relevant to the data type used in this paper, similar methods have been employed to predict corruption using local budgets (Ash, Galletta and Giommoni, 2025) and to analyze trends in policy determinants in US localities (Ash and Galletta, 2024). Moreover, our work builds upon recent studies that employ cosine similarity in the financial allocation of assets. For instance, Girardi et al. (2021) investigates the impact of portfolio (cosine) similarity on asset liquidation among insurance companies. This study finds that a higher degree of similarity in portfolio holdings correlates with more frequent asset sales during financial shocks, which can significantly influence market prices.

Finally, we provide additional evidence supporting the theory of a political business cycle (Nordhaus, 1975). Most evidence indicates that under certain conditions, politicians manipulate budgets such that, closer to elections, public expenditure increases while taxes might decrease. This often results in a negative impact on public debt and deficits (Akhmedov and Zhuravskaya, 2004; Alesina and Paradisi, 2017; Repetto, 2018; Ferraresi, 2020). Other models suggest that politicians adjust the composition of spending, not the overall budget, to signal their priorities to voters (Drazen and Eslava, 2010).

The remainder of the paper is organized as follows. Section 2 provides the institutional background and presents the data. Section 3 details the methodology for computing similarity in policymaking and local characteristics, and tests the validity of our metric. Section 4 introduces and estimates our measure of policy divergence. Section 5 discusses the results of the empirical application concerning the political budget cycle. Finally, Section 6 offers concluding remarks and summarizes the key findings.

2. Institutional background and Data

2.1. Institutional background

Italy's sub-national government features a three-tier system: 20 regions (regioni), 110 provinces (province), and approximately 8,000 municipalities (comuni). This study focuses on the municipal level, the lowest administrative unit. Each municipality (comune) has a mayor (sindaco), an executive committee (giunta) appointed by the mayor, and an elected city council (consiglio comunale) that approves the annual budget proposed by the mayor.

Municipalities in Italy are responsible for several public services, such as waste disposal, local transportation, social services, childcare and primary schooling, urban road maintenance and cleaning, water and sewer services, environmental monitoring and protection, planning and zoning. Municipal revenues consist of various sources, including tax revenues derived from income taxes, real estate taxes, and taxes related to services like waste management. Additionally, transfer revenues originate from the national or regional governments, as well as from the European Union (EU). On the expenditure side, current expenses pertain to the municipality's day-to-day operational costs, such as salaries and utilities. Capital expenditures, on the other hand, are investments allocated to projects that typically extend beyond a single budget year and are primarily associated with infrastructure development, such as the construction of roads and schools.

The current framework for municipal elections in Italy applies the direct election of mayors and the plurality rule, with variations based on city size. In municipalities with populations below 15,000, elections use a single ballot and plurality rule. In cities with a population exceeding 15,000, a dual ballot system is employed. Since 1993, mayors in Italy have been subject to a two-term limit[1]. In 2000, the length of the mayoral term was prolonged from four to five years. The number of city councilors varies based on the size of the municipality.

2.2. Data

We compiled a novel dataset from several sources. First, we gathered municipal budget data for the 2000-2015 period from the Ministry of Economy and Finance for all 8,000 Italian municipalities. Our dataset provides information on the complete composition of local budgets. In particular, we use data on both revenue and expenditure.[2] For expenditures, each variable specifies whether they are commitments, payments in current account competence, or payments in residual accounts. Similarly, for revenues, we account for assessments, collections in current account competence, and collections in residual accounts. While the budget composition changes slightly each year, it remains consistent across municipalities for any given year. Notably, there were significant changes in 2008, which we will detail in our analysis.

The second main source is the Italian decennial census, providing a comprehensive overview of the demographic and economic composition of each municipality. We include variables related to housing and living conditions, mobility and transportation, economic indicators, environmental and urban quality, and demographic and migration dynamics. The complete list of these variables is presented in Appendix Table A.1. All census-based variables are taken from the 2011 wave and are therefore treated as time-invariant in the analysis.

Finally, we incorporated information about local politics from the "Anagrafe degli Amministratori Locali e Regionali" database of the Ministry of Interior. This dataset includes details on the gender, educational attainment, and party affiliation of the mayor, as well as the year of elections.

[1] Since 2014 a reform (Law April 2014 no.56) allows mayors in municipalities with less than 3,000 inhabitants to re-run for a third term, whereas mayors in cities with a number of residents above the cut-off still face a two-term limit.

[2] Italian local budgets are divided into sections (*quadri*). Our data is sourced from *quadro 2*, *quadro 4*, and *quadro 5*.

3. Similarity in Fiscal Policy and Local Characteristics

3.1. The Similarity Index

In this section, we introduce our measure of similarity. Our goals are twofold: first, to create a metric that shows how similar the policymaking of a pair of municipalities is, and second, to develop a measure that indicates how close their socio-demographic characteristics are. To generate these measures, we want to consider the high-dimensionality of both parameters of interest. Indeed, the policymaking of a municipality is not just proxied by the size of the budget or the allocation in macro categories but rather by a more fine-grained allocation. Additionally, local demographics are not just a matter of, for example, population size or age distribution but include several other important municipal characteristics. For this reason, drawing from the recent literature in applied machine learning and Natural Language Processing (NLP) techniques, we chose to use the cosine similarity index.

This similarity metric measures the cosine of the angle between two non-zero vectors in a multidimensional space. It assesses how similar the two vectors are by focusing on their direction rather than their magnitude. The value ranges from -1 to 1, where 1 indicates identical direction, 0 indicates orthogonality (no similarity), and -1 indicates completely opposite direction. However, when all vectors have elements that are non-negative, as in our case for the budget, this measure of similarity is bounded in the interval [0,1].

$$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \, \|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} a_i \cdot b_i}{\sqrt{\sum_{i=1}^{n} (a_i)^2} \sqrt{\sum_{i=1}^{n} (b_i)^2}} \tag{1}$$

Formally, we compute the cosine similarity between vectors **A** and **B** and divide it by the product of their magnitudes. The dot product is the sum of the products of corresponding elements (a_i and b_i) of the two vectors. The magnitudes are calculated as the square root of the sum of the squares of the elements of each vector as reported in Equation (1).[3]

For our purposes, the vectors of interest for assessing similarity in policymaking will

[3] It is worth highlighting that the cosine similarity formula is closely related to the Pearson correlation coefficient when applied to centered vectors (variables).

be derived from the budget accounts, where each item is expressed as a proportion of the total revenue or expenditure, depending on the item's category. This means that, eventually, we will have a single vector for each municipality-year. Conversely, the vectors representing municipal characteristics will consist of individual elements that correspond to specific attributes of the municipalities. In this case, we account only for the cross-sectional variation, as most of the characteristics come from the decennial census and, therefore, lack the desired temporal variation. Vectors (2) and (3) are simple examples of what is included as the values in the vectors.

Budget Vector

$$\begin{pmatrix} \text{Share Taxes (Rev.)} \\ \text{Share Prop. Tax (Rev.)} \\ \text{Share Prop. Tax First Res. (Rev.)} \\ \text{Share Prop. Tax Oth. Buil. (Rev.)} \\ \vdots \\ \vdots \\ \text{Share Acqui. of Real Estate (Exp)} \\ \text{Share Acqui. Machinery (Exp)} \\ \text{Share Ext. Prof. Assig. (Exp)} \\ \text{Share Capital Contr. (Exp)} \end{pmatrix} \tag{2}$$

Characteristics Vector

$$\begin{pmatrix} \text{Population} \\ \text{Share of Employed} \\ \text{Share of highly educated} \\ \text{Share of foreigners} \\ \vdots \\ \vdots \\ \text{Population Density} \\ \text{Literacy Rate} \\ \text{School Dropout} \\ \text{Divorce rate} \end{pmatrix} \tag{3}$$

It is important to highlight that by using vector representation and cosine similarity as our measure of interest, we abstract away from potential differences in the relative importance of each component in policy formulation.[4]

3.2. Generating the Similarity Measures

We construct two distinct measures of similarity. The first captures similarities in policymaking by analyzing the detailed structure of municipal budgets, reflecting local governments' fiscal decisions and priorities. The second measures socio-demographic similarity, summarizing how municipalities compare in terms of population structure and socioeconomic conditions.

To generate similarities in policymaking, we analyze the complete structure of the budgets.[5] The number of components differs across years; Table A.2 offers a detailed overview of the final number of budget variables employed in each year. Overall, we have more information on the expenditure side rather than the revenue side. We can also see a marked increase in the number of expenditure features in the year 2008. This variation

[4]In this approach, each component is treated with equal weight, implying that all elements contribute equally to the overall similarity measure. This approach might introduce "measurement error" in the similarity estimates, as we could underweight highly relevant components or overweight less relevant ones. We abstain from introducing differential weights as this could be seen as arbitrary, unless there is a clear rationale for assigning specific importance to particular components.

[5]For computational purposes, we exclude only those variables with missing values for all municipalities in a given year.

in budgetary components is important to keep in mind, as it implies that the generated similarity measure primarily offers a cross-sectional interpretation of policy similarity. Primarily for computational reasons, we generate similarity measures only for pairs of municipalities within the same region and for a given year.

We provide some simple descriptive results in Figure A.1. Figure A.1, Panel a, shows the trend of average budget similarity over the years from 2000 to 2015. The data reveal a relatively stable pattern of similarity until 2008, followed by a noticeable decline. Such a drop is likely due to a change in the budget structure, i.e., the increase in the number of features, as reported in the previous paragraph. After 2008 we show a slight decrease in subsequent years. Figure A.1, Panel b, shows the average budget similarity for the period 2000-2015 for every Italian region. Average budget similarity ranges from approximately 0.45 to 0.8, with most regions falling between 0.55 and 0.65. There is, however, some heterogeneity across the regions, with Valle d'Aosta having the highest similarity score (roughly 0.8) and Abruzzo having the lowest average similarity (approximately 0.45).

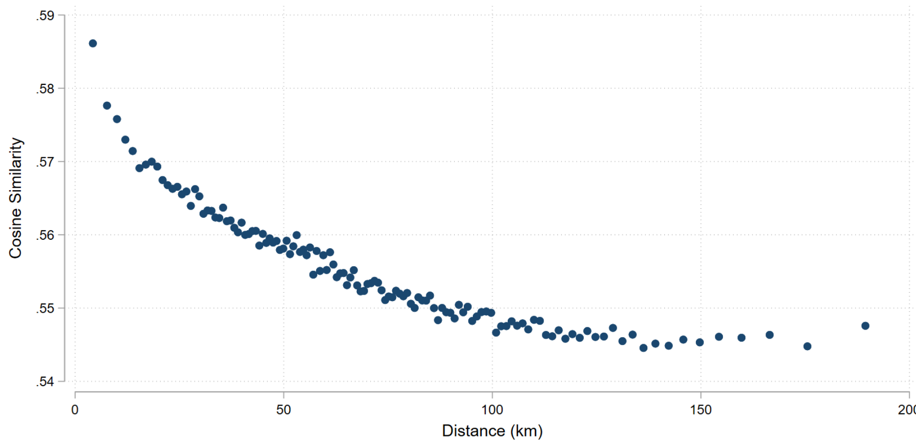
To measure similarity in socio-demographic characteristics, we account for variables related to housing and living conditions, mobility and transportation, economic indicators, environmental and urban quality, and demographic and migration dynamics. In this case, we have selected 60 variables relevant to describing a municipality's population structure (see Appendix Table A.1). As in the previous exercise, each variable is treated as a vector component representing a municipality's socio-demographic characteristics. In this case, we standardized the variables by region, as this is the level at which we ultimately generate our predictions to calculate the divergence measure.

3.3. A validation exercise

In this section, we provide evidence supporting the validity of our measure of policymaking similarity by analyzing its correlation with the similarity in socio-demographic and political characteristics known to be important determinants of policymaking. By examining these relationships, we aim to demonstrate that municipalities with similar profiles tend to have more similar budget structures, thereby validating our cosine similarity index as an effective measure of policymaking similarity.

We begin our analysis by examining the relationship between the cosine similarity

Figure 1: Binscatter Budget Similarity vs Geographical Distance



Note: The binscatter plot illustrates the relationship between the cosine similarity of municipal budgets and the geographical distance between municipalities. Each point represents an aggregated average of budget similarity and distance in kilometers by municipalities.

index and geographical distance, a critical factor discussed in public finance literature.[6] Figure 1 presents a binscatter plot that illustrates a negative correlation between budget similarity and the distance between pairs of municipalities. This finding supports the hypothesis that geographical proximity influences budgetary decisions. Municipalities that are farther apart tend to exhibit greater differences in other characteristics, as evidenced by lower cosine similarities in their budgets.

We complement the previous evidence by estimating the following regression model:

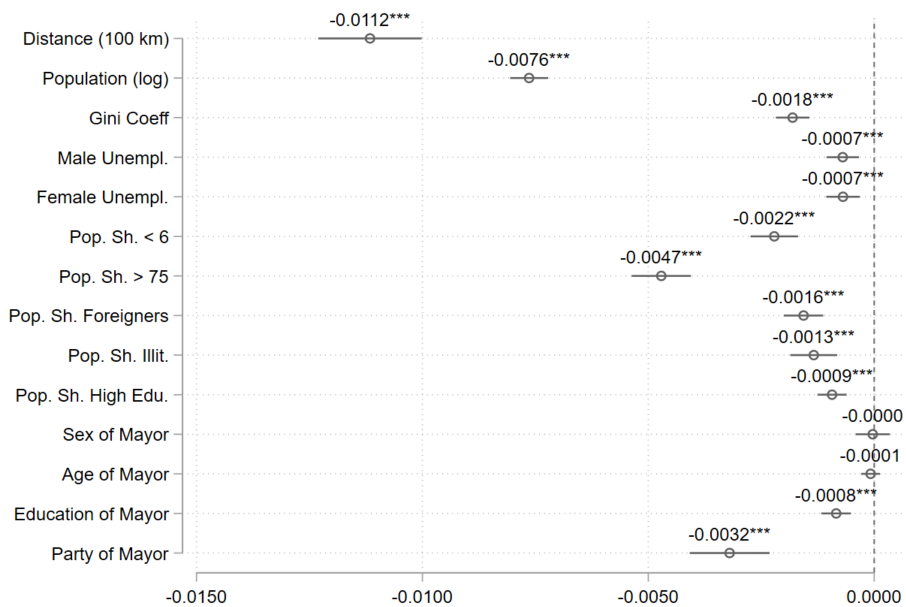
$$\text{Policy Similarity Index}_{ij,t} = \alpha + \beta_m X^m_{ij,t} + \mu_i + \delta_j + \epsilon_{ij} \tag{4}$$

where Policy Similarity Index$_{ij,t}$ is the cosine similarity index between municipalities i and j at time t within the same region, $X^m_{ij,t}$ is the difference in the value of our set of $m \in M$ covariates. Specifically, it represents the standardized absolute difference between each pair of municipalities of the following variables: distance (in 100 km), population (log-transformed), Gini coefficient, male and female unemployment rates, population shares under 6 and over 75 years, the share of foreign residents, illiteracy rate,

[6]A large body of work documents strategic interaction in local policy choices (Brueckner, 1998; Bordignon, Cerniglia and Revelli, 2003), tax mimicking and yardstick competition (Buettner, 2001; Allers and Elhorst, 2005; Bosch and Solé-Ollé, 2007), and expenditure spillovers (Solé-Ollé, 2006), as well as spatial patterns in local efficiency and taxation (Revelli, 2007, 2001).

share of highly educated population as well as sex, age, education, and party affiliation of the mayor. In addition, we include municipality i and municipality j fixed effects (i.e., μ_i and δ_j). ϵ_{it} is the error term. The municipalities' fixed effects allow us to exploit within-individual variations over different pairings. In other words, we compare how the difference in a given variable between two municipalities relates to the difference in the same variable among other municipality pairs, thereby controlling for all unobserved variables that are constant for each municipality but vary across municipalities.[7] For our exercise, we focus only on the year 2011, which is a population census year.

Figure 2: Validation Policy Similarity



Note: This graph shows the coefficients and confidence intervals of various municipal characteristics differences between a pair of municipalities (standardized) on their fiscal policy similarity. The stars denote significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The x-axis shows the magnitude of the coefficients, while the y-axis lists the variables. The error bars represent the 95% confidence intervals for each coefficient.

We present our results graphically in Figure 2. We observe that the sign of the coefficients always points in the expected direction: municipalities with greater differences in demographic and population composition, as well as mayoral characteristics, tend to

[7]This approach is similar to the estimation of gravity models of trade in international economics, where country$_i$ and country$_j$ fixed effects are included in a dyadic regression. However, since our analysis does not involve time-varying characteristics, we do not include dyadic fixed effects (Anderson and Van Wincoop, 2003).

exhibit lower similarities in their resource allocation and budget structure.

In particular, we find that distance and population size emerge as the most significant predictors, confirming the importance of geographic factors and simple population characteristics. The significant impact of other populations' features further stresses the role of socio-economic in shaping local policies. Another important predictor of policy similarity is, consistent with the expected role of political preferences, the political affiliation of mayors. Conversely, the lack of significant effects of the age and sex of mayors suggests that the individual attributes of leaders are less critical compared to their political and policy orientations. This is interesting considering existing research that frequently identifies significant causal effects of a mayor's gender or age on various economic and social dimensions (Brollo and Troiano, 2016; Alesina, Cassidy and Troiano, 2019; Bochenkova, Buonanno and Galletta, 2023).

Overall, we provide supporting evidence about the validity of our cosine similarity index as a measure of policymaking similarity, reflecting how comparable socio-demographic and political attributes lead to analogous budgetary decisions.

4. A Measure of Fiscal Divergence

In this section, we construct a measure of fiscal divergence by quantifying how much municipalities deviate from the expected fiscal behavior of their socio-demographically similar peers. The intuition underlying our approach is straightforward: municipalities sharing similar characteristics are expected to make similar policy choices. Thus, substantial departures from these expected choices indicate that a municipality is pursuing unconventional or unexpected policies.

We argue that one effective way to measure policy divergence is to estimate a model that accurately predicts policymaking similarity based on similarities in local characteristics. By using this approach, we can derive the expected fiscal behavior of municipalities sharing similar socioeconomic profiles and identify cases where actual policies significantly deviate from these expectations. To achieve this, we move beyond the validation exercise of the previous section and utilize a more comprehensive representation of local characteristics. This involves using the similarity index in local characteristics discussed in section 3.2, which accounts for 60 different variables, and estimate the following regression model separately for each region r and year t:

$$\text{Policy Similarity Index}_{ij} = \alpha + \beta\text{Local Characteristics Similarity Index}_{ij} + \alpha_i + \delta_j + \epsilon_{ij} \tag{5}$$

where most of the variables are defined similarly to those in Equation (4). Specifically, the Policy Similarity Index$_{ij}$ denotes the similarity in policymaking between municipalities i and j. Our key independent variable is the Local Characteristics Similarity Index$_{ij}$, representing the cosine similarity of the highly dimensional set of municipal characteristics presented in Table A.1. The terms α_i and δ_j account for fixed effects for municipality i and municipality j, respectively, while ϵ_{ij} captures the error term. Also, in this case, including fixed effects allows for controls for unobserved, invariant characteristics specific to each municipality, thereby isolating the impact of variations in local characteristics similarity across municipalities on policy similarity.

As we are interested in assessing the quality of the predictive power of the model, besides the actual estimation of β, we use a cross-validation approach where the dataset is divided into five folds. Iteratively, we hold out one fold as the test set and train our model on the remaining four folds, which constitute the training set. Therefore, we estimate 1,600($=r \times t \times 5$) different equations.

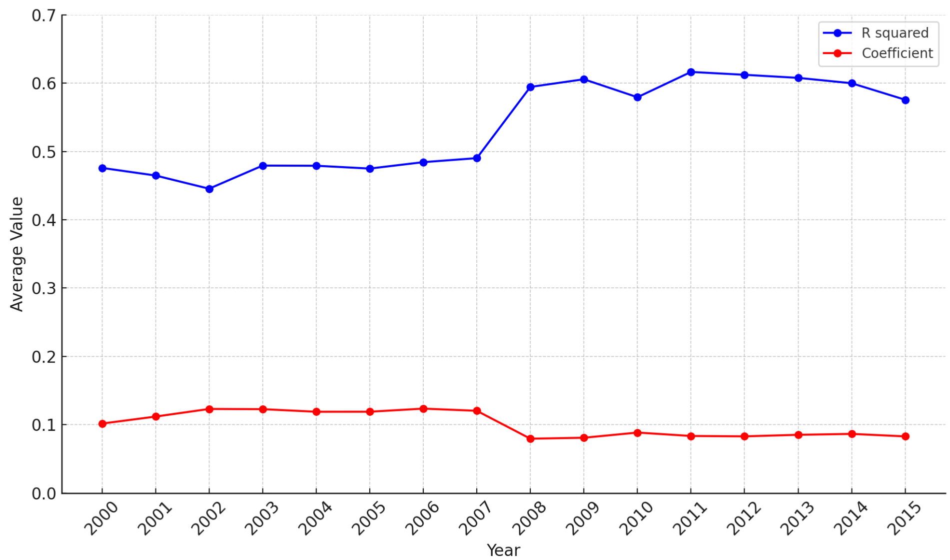
We present the detailed results of our estimations for each region and year in Appendix Table A.3, which includes the coefficients and the R-squared values, representing the model's out-of-sample predictive performance, average across the five folds. We report graphically some more general results in Figure 3. The results demonstrate variability over time (Figure 3 Panel a) and across different regions (Figure 3 Panel b) concerning the magnitude of the coefficients and R-squared values, confirming the need for a flexible specification in the model estimation. On average, across the entire dataset, we find an R-squared value of 0.536 and a coefficient of 0.100, always significant at the 1% level. This suggests that increasing the local characteristics similarity by one standard deviation will result in a 0.10 standard deviation increase in policymaking similarity. The R-squared value indicates a good, albeit not perfect, fit of the model.

A crucial feature of our estimated model is that, when ranking municipalities by the outcome variable—specifically, policymaking similarity—the rankings closely align with those obtained from the predicted outcome variable. We confirm this using a calibration plot, as shown in Figure 4.

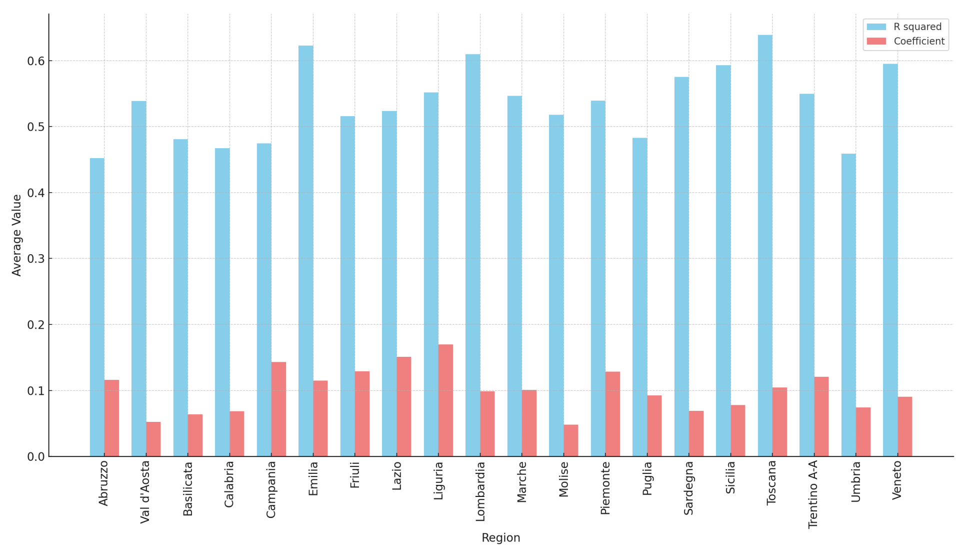
Having validated the quality of the model, we now move to assess the potential

Figure 3: R-squared and Coefficients - Time and Geographical Variation

(a) Time

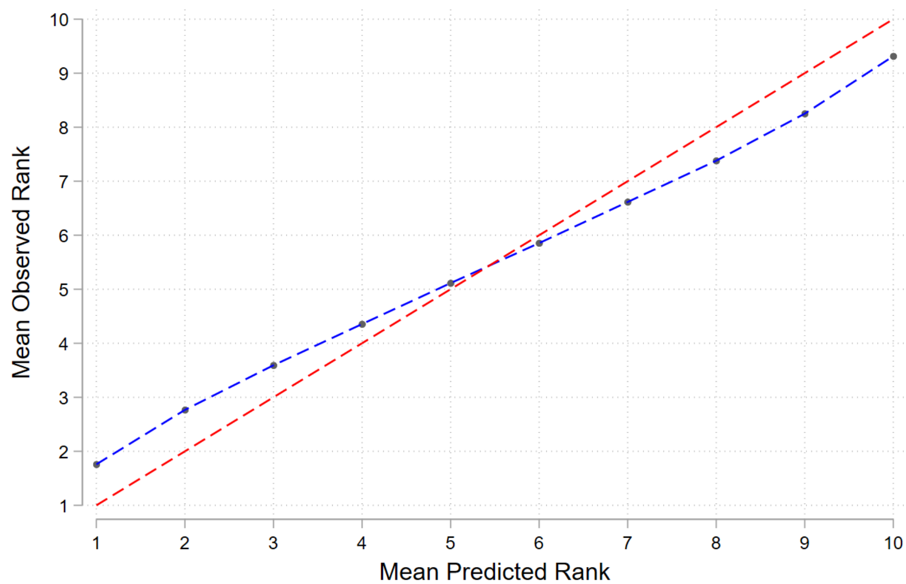


(b) Region



Notes: This figure reports the temporal and geographical variations in the estimations. The graph in panel (a) shows how the R-squared and the coefficient vary over time, averaged across all regions. The graph in panel (b) show how the R-squared and the coefficient vary across regions, averaged across all years.

Figure 4: Calibration Plot



Note: The calibration plot compares predicted ranks with observed ranks. Points represent mean ranks in each bin. The dashed red line indicates perfect calibration.

deviation in policymaking by looking at the errors/residuals of the model. Therefore, we compute the difference between the observed and predicted value from the model $r_{ij} = y_{ij} - x_{ij}\hat{\beta}$, for each region r and year t. In other words, the residuals indicate the gap between a specific municipality's policy implementation and the expected one based on its characteristics. Since our model was estimated using municipality pairs over specific years, the predicted outcomes and residuals were calculated at that level of granularity. For simplicity, we shift our focus to an observation level that considers each municipality individually over time. We achieve this by averaging the residuals for each municipality by year.

Appendix Figure A.2 presents the geographical distribution of policy divergence across various Italian regions, with darker colors identifying the areas with higher values of aggregated fiscal divergence. We can see that there is variation across region and time, with the southern regions, along with Sardegna and Sicilia, experiencing rising divergence between 2005 and 2015. In Northern and Central Italy, the trend is more heterogeneous, without a clear direction.

5. Application: Fiscal Divergence and Electoral Incentives

We then examine whether our divergence measure for policy experimentation is affected by electoral incentives by testing for the presence of Political budget cycles (PBCs).

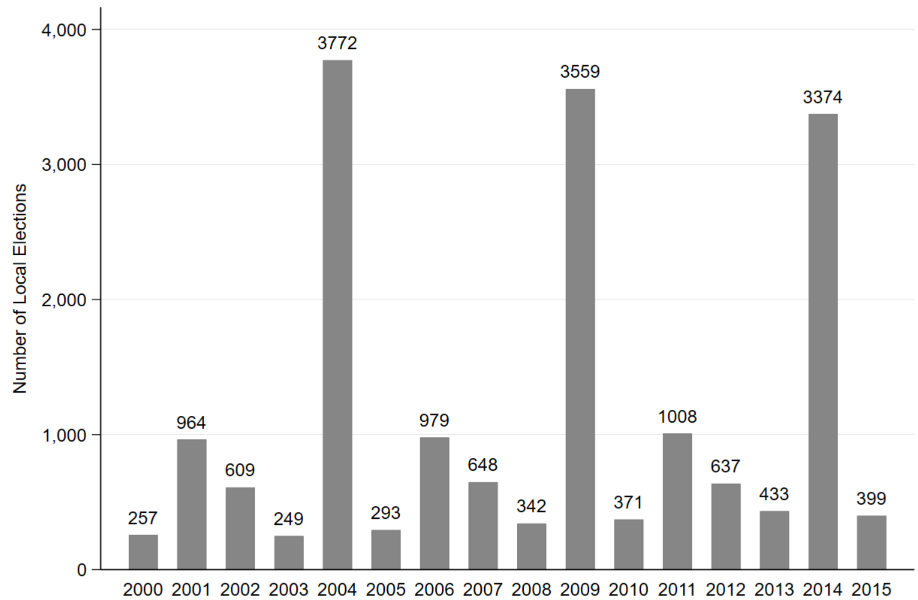
PBCs arise from politicians' tendency to manipulate fiscal policies to gain electoral advantage. For instance, Nordhaus (1975) proposes that governments exploit a Phillips curve trade-off, implementing stimulatory policies before elections to attract votes from myopic voters. Similarly, Rogoff and Sibert (1988) argue that politicians signal their competence by increasing spending before elections. Building on this, Shi and Svensson (2006) further argue that all politicians, regardless of competence, may boost public goods provision before elections to influence uninformed voters, with stronger cycles observed in developing countries. Offering a different perspective, Drazen and Eslava (2010) suggest that in established democracies with informed voters, PBCs arise not from perceived competence but from politicians' manipulation of spending preferences. In this view, politicians may adjust the composition of spending to align with voter priorities, thereby signaling alignment with public interests. Although citizens may not have detailed knowledge of the specific budget breakdowns, they can still sense the impact of fiscal decisions through their experience of public goods and taxation.

In this framework, our divergence index serves as an indicator of the perceived gap between actual budget outcomes and what citizens expect or desire in terms of public services and fiscal policies. Therefore, we expect that our divergence measure decreases just before the election. The analysis uses the staggered election schedules of over 8,000 Italian municipalities. The staggered timing results from historical factors and from instances in which government crises led to the premature end of electoral mandates before their scheduled deadlines. As suggested by previous research exploiting these features of the Italian local political system, exogenous timing helps separate the impact of the electoral cycle from the effects of events occurring in a given year and other confounders (Repetto, 2018). Figure 5 shows the number of elections by year.

Formally, we estimate the following equation:

$$\text{Divergence Index}_{iyt} = \beta_k \sum_{k=0}^{4} \text{Electoral Cycle}_{iy,t-k} + \mu_i + \epsilon_{iyt} \tag{6}$$

Figure 5: Number of Municipal Elections by Year



Note: The figure displays the number of municipal elections held each year.

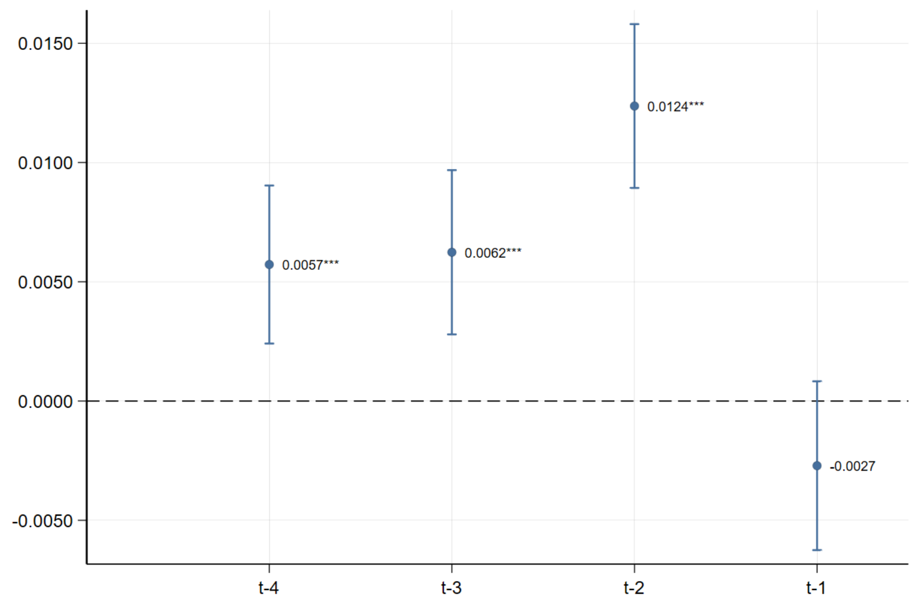
where Divergence Index_{iyt} is the dependent variable representing the fiscal divergence index for municipality i in year y at time t. The term $\beta_k \sum_{k=0}^{4}$ Electoral $\text{Cycle}_{iy,t-k}$ captures the effects of each year within the electoral cycle, from the election year ($k = 0$) to the year before the next election ($k = 4$). We include municipality fixed effects μ_i, and finally, ϵ_{iyt} represents the error term, which is clustered at the municipality level.[8]

Our main results are illustrated in Figure 6, which graphically displays the estimated coefficients for each year relative to the election year. The evidence indicates that deviations are significantly higher during the first three years after elections, while they are either absent or negative in the year preceding elections. This suggests that local officials tend to move their policies closer to the expected demographic-based needs of the population as elections approach, whereas in the periods immediately following elections, policies tend to be less in line with these needs.

Our measure of fiscal divergence serves as a proxy for how closely politicians adhere to the anticipated budget behavior of their constituency. Thus, our analysis can be interpreted as both a test and a confirmation of the model proposed by Drazen and

[8]We do not include year fixed effects or year $\times$ region fixed effects, as the outcome variable has been constructed to inherently account for variations within years and across year $\times$ region interactions.

Figure 6: Political Incentives and Fiscal Divergence



Note: The figure displays the coefficients and confidence intervals from Regression 6 for every year of the electoral cycle.

Eslava (2010). Moreover, the results are also consistent with previous evidence that politicians are less likely to engage in experimental policies shortly before elections due to the risk of unfavorable outcomes (Bernecker, Boyer and Gathmann, 2021).

6. Conclusion

In this paper, we developed a novel approach to measuring policy experimentation at the local level using comprehensive municipal budget data. By analyzing budget similarities across roughly 8,000 Italian municipalities from 2000 to 2015, we introduced a measure of policy divergence as deviations from predicted fiscal behaviors of municipalities with similar socio-demographic. Our method provides a clear and practical metric for capturing when local governments engage in unexpected policy actions. We validated our measure by demonstrating its sensitivity to political incentives in an empirical application on the political budget cycle. Specifically, we showed that municipalities systematically reduce experimentation in the year preceding elections, consistent with politicians avoiding risky policy choices during politically sensitive periods.

In sum, our paper makes three key contributions. First, we develop a data-driven, model-free measure of fiscal policy divergence that captures the extent to which local governments' budget allocations deviate from expectations based on socio-demographic characteristics. This approach allows us to analyze the entire composition of fiscal policy, rather than focusing on individual budget categories in isolation. Second, we show that our method provides a flexible and consistent benchmark for cross-jurisdictional comparisons, allowing researchers to detect and quantify unexpected fiscal behaviors across a wide variety of contexts. Finally, through an application to Italian municipalities, we demonstrate the empirical relevance of our measure by documenting that fiscal divergence systematically declines before elections, shedding light on how electoral incentives shape local policymaking.

Future studies could extend our methodology to explore how other institutional, economic, or informational factors influence policy divergence across diverse settings.

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Appendix

Table A.1: List of Socio-Demographic Variables

Variable Name	Variable Name	Variable Name
Population	Male Labor Parti.	Density
Incidence of Homeowners	Female Labor Parti.	Population Under 6
Housing Age	Labor Activity Rate	Population Under 75
Living Area (sq m)	Municipal Unempl.	Old Age Dependency
Housing Crowding	Functional Unempl.	Divorce Rate
Family Size	Welfare Renewals	Foreign Nationals
Elderly Living Alone	Agricultural Empl.	Foreign Minors
Illiteracy Rate	Manufacturing Empl.	Foreign Empl.
Education 15-19	Trade Empl.	Social Vulnerability
Job Mobility	High Skill Empl.	Avg. Size Household
Study Mobility	Manual Labor Empl.	Internal Migration Net
Private Mobility	Low Skill Empl.	Internal Migration Male
Public Mobility	Job-Related Mobility	Internal Migration Female
No City Center	Study-Related Mobility	
Urban Density	Private Trans. Mobility	
Building Density	Public Trans. Mobility	
Young Families	Dropouts	
School Dropouts	Building Age	
Migration Population	Migration Segregation	
Employed Immigrants	Income Below Poverty	
Income \$0-\$10k	Income \$10k-\$15k	
Income \$15k-\$26k	Income \$26k-\$55k	
Income \$55k-\$75k	Income \$75k-\$120k	
Income Above \$120k		

Note: The table reports the municipal variables used to calculate similarity in socio-demographic characteristics across municipalities.

Table A.2: Budget Components used in Cosine Similarity Computation for the Years 2000-2015

Year	**Number of Revenue Components**	**Number of Expense Components**
2000	251	2331
2001	263	2331
2002	266	2331
2003	261	2331
2004	261	2331
2005	261	2331
2006	278	2331
2007	271	2394
2008	297	4158
2009	315	4155
2010	315	4185
2011	330	4185
2012	324	4185
2013	339	4245
2014	345	4205
2015	345	4205

Note: The table reports the number of variables used to calculate similarity in policymaking across municipalities by year and type of component.

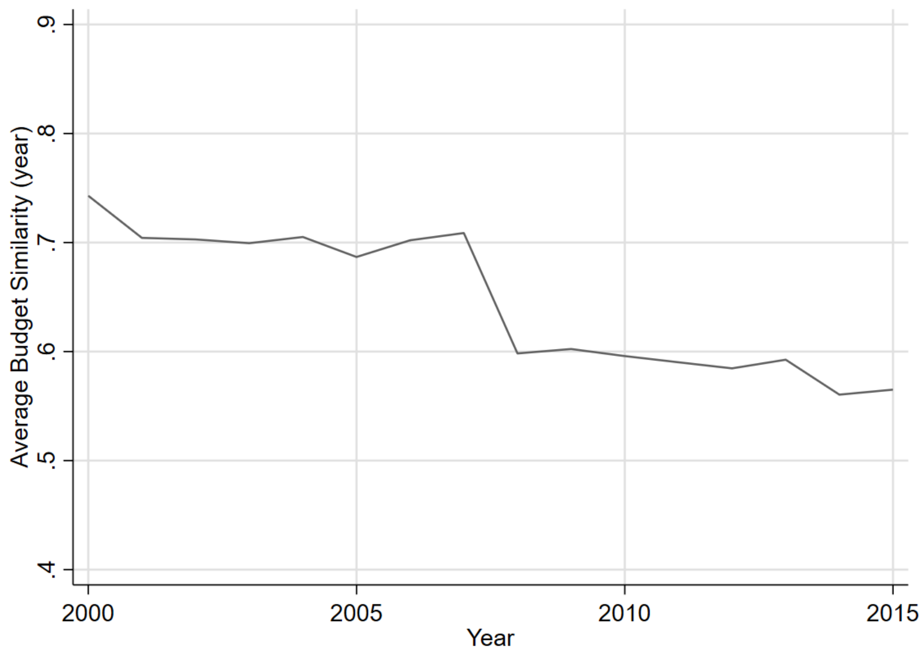
Table A.3: Regression Results - Average Values by Year and Region

Region	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
	0.359	0.469	0.405	0.430	0.440	0.442	0.471	0.469	0.560	0.478	0.547	0.507	0.461	0.351	0.422	0.426
Abruzzo	0.127	0.093	0.111	0.111	0.123	0.126	0.150	0.137	0.092	0.112	0.095	0.113	0.124	0.124	0.120	0.097
	0.016	0.012	0.012	0.016	0.011	0.012	0.014	0.013	0.010	0.015	0.012	0.013	0.014	0.017	0.014	0.013
	0.301	0.307	0.390	0.540	0.498	0.460	0.319	0.519	0.515	0.664	0.453	0.545	0.704	0.831	0.760	0.815
Val d'Aosta	0.062	0.055	0.038	0.051	0.043	0.048	0.075	0.065	0.030	0.038	0.059	0.047	0.035	0.067	0.066	0.059
	0.028	0.023	0.009	0.019	0.011	0.012	0.021	0.017	0.014	0.011	0.020	0.015	0.006	0.012	0.014	0.012
	0.368	0.367	0.360	0.423	0.321	0.361	0.409	0.459	0.564	0.610	0.504	0.551	0.641	0.580	0.554	0.623
Basilicata	0.038	0.071	0.063	0.081	0.055	0.092	0.070	0.070	0.058	0.063	0.066	0.058	0.057	0.076	0.049	0.052
	0.009	0.016	0.011	0.011	0.011	0.012	0.010	0.011	0.011	0.010	0.013	0.012	0.008	0.013	0.008	0.010
	0.511	0.382	0.407	0.435	0.334	0.427	0.424	0.406	0.589	0.548	0.494	0.592	0.579	0.406	0.477	0.466
Calabria	0.054	0.065	0.086	0.091	0.075	0.086	0.087	0.096	0.047	0.051	0.068	0.048	0.043	0.071	0.069	0.059
	0.006	0.007	0.007	0.008	0.006	0.008	0.007	0.007	0.004	0.005	0.007	0.005	0.003	0.009	0.007	0.007
	0.369	0.375	0.336	0.393	0.391	0.397	0.453	0.444	0.630	0.609	0.480	0.610	0.632	0.553	0.481	0.438
Campania	0.139	0.137	0.244	0.202	0.178	0.163	0.181	0.206	0.098	0.079	0.127	0.095	0.088	0.094	0.141	0.119
	0.011	0.012	0.017	0.014	0.012	0.011	0.012	0.012	0.005	0.005	0.010	0.006	0.005	0.007	0.012	0.011
	0.524	0.540	0.521	0.586	0.607	0.584	0.594	0.572	0.667	0.670	0.668	0.691	0.655	0.659	0.725	0.699
Emilia	0.119	0.132	0.167	0.144	0.155	0.133	0.106	0.129	0.095	0.090	0.100	0.105	0.115	0.095	0.080	0.075
	0.009	0.013	0.014	0.014	0.014	0.013	0.010	0.011	0.008	0.008	0.009	0.008	0.009	0.008	0.007	0.007
	0.406	0.420	0.449	0.385	0.389	0.481	0.485	0.534	0.622	0.550	0.609	0.562	0.516	0.587	0.671	0.585
Friuli	0.135	0.142	0.138	0.164	0.164	0.179	0.165	0.165	0.092	0.091	0.114	0.105	0.097	0.100	0.108	0.102
	0.013	0.013	0.013	0.019	0.016	0.016	0.014	0.014	0.007	0.010	0.010	0.009	0.011	0.011	0.010	0.009
	0.421	0.419	0.410	0.386	0.389	0.440	0.488	0.454	0.566	0.547	0.622	0.664	0.661	0.686	0.640	0.582
Lazio	0.169	0.220	0.189	0.195	0.197	0.209	0.222	0.231	0.113	0.112	0.091	0.105	0.086	0.094	0.092	0.091
	0.013	0.017	0.015	0.016	0.014	0.014	0.015	0.018	0.010	0.010	0.006	0.007	0.006	0.007	0.007	0.008
	0.544	0.373	0.426	0.434	0.416	0.448	0.480	0.484	0.667	0.656	0.677	0.686	0.691	0.651	0.636	0.560
Liguria	0.194	0.263	0.236	0.241	0.217	0.217	0.230	0.204	0.121	0.125	0.113	0.124	0.104	0.121	0.103	0.105
	0.016	0.025	0.019	0.020	0.017	0.016	0.018	0.017	0.007	0.009	0.008	0.009	0.008	0.009	0.009	0.010
	0.562	0.527	0.528	0.539	0.566	0.547	0.575	0.598	0.664	0.673	0.637	0.675	0.679	0.662	0.671	0.655
Lombardia	0.106	0.127	0.142	0.131	0.128	0.105	0.110	0.099	0.081	0.081	0.093	0.081	0.076	0.075	0.070	0.072
	0.007	0.008	0.008	0.007	0.007	0.006	0.006	0.006	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004
	0.340	0.427	0.364	0.436	0.522	0.555	0.521	0.554	0.664	0.640	0.629	0.654	0.629	0.599	0.584	0.625
Marche	0.147	0.138	0.163	0.118	0.149	0.136	0.143	0.119	0.055	0.068	0.072	0.059	0.058	0.065	0.059	0.062
	0.018	0.018	0.018	0.015	0.016	0.012	0.015	0.013	0.007	0.008	0.007	0.008	0.008	0.008	0.009	0.009
	0.501	0.613	0.364	0.484	0.545	0.498	0.406	0.429	0.593	0.622	0.619	0.594	0.527	0.480	0.438	0.573
Molise	0.053	0.057	0.059	0.055	0.066	0.067	0.075	0.073	0.041	0.038	0.031	0.032	0.029	0.032	0.029	0.037
	0.007	0.007	0.009	0.007	0.010	0.008	0.011	0.010	0.006	0.005	0.005	0.006	0.005	0.007	0.008	0.008
	0.572	0.414	0.430	0.400	0.423	0.481	0.499	0.475	0.593	0.610	0.616	0.655	0.659	0.632	0.629	0.544
Piemonte	0.127	0.155	0.170	0.171	0.163	0.167	0.175	0.156	0.111	0.113	0.105	0.096	0.095	0.088	0.083	0.085
	0.007	0.010	0.009	0.009	0.009	0.009	0.009	0.009	0.006	0.006	0.006	0.005	0.005	0.004	0.004	0.006
	0.580	0.394	0.340	0.471	0.454	0.428	0.396	0.373	0.517	0.583	0.458	0.565	0.550	0.570	0.599	0.445
Puglia	0.095	0.079	0.117	0.110	0.088	0.110	0.119	0.116	0.081	0.076	0.090	0.081	0.086	0.069	0.079	0.081
	0.013	0.013	0.015	0.012	0.012	0.017	0.017	0.016	0.010	0.010	0.013	0.010	0.012	0.008	0.009	0.013
	0.609	0.555	0.522	0.658	0.730	0.450	0.508	0.413	0.523	0.591	0.602	0.636	0.629	0.673	0.643	0.458
Sardegna	0.076	0.068	0.066	0.077	0.055	0.062	0.084	0.097	0.063	0.056	0.081	0.057	0.070	0.056	0.067	0.063
	0.010	0.009	0.008	0.011	0.007	0.010	0.010	0.012	0.009	0.007	0.010	0.007	0.008	0.006	0.008	0.009
	0.597	0.618	0.561	0.484	0.514	0.416	0.510	0.519	0.665	0.684	0.690	0.649	0.611	0.645	0.654	0.667
Sicilia	0.074	0.084	0.081	0.097	0.091	0.087	0.088	0.105	0.057	0.063	0.063	0.070	0.077	0.070	0.071	0.065
	0.006	0.007	0.007	0.008	0.007	0.007	0.007	0.008	0.005	0.005	0.005	0.005	0.006	0.005	0.005	0.005
	0.584	0.579	0.632	0.654	0.643	0.560	0.640	0.625	0.678	0.676	0.641	0.664	0.647	0.645	0.665	0.688
Toscana	0.087	0.104	0.109	0.126	0.121	0.120	0.113	0.088	0.096	0.115	0.097	0.099	0.106	0.091	0.094	0.106
	0.009	0.009	0.010	0.010	0.011	0.010	0.008	0.008	0.007	0.008	0.008	0.007	0.009	0.007	0.008	0.007
	0.428	0.584	0.542	0.573	0.519	0.501	0.507	0.525	0.549	0.557	0.532	0.585	0.618	0.627	0.590	0.560
Trentino A-A	0.075	0.084	0.086	0.097	0.119	0.111	0.106	0.092	0.121	0.132	0.142	0.126	0.131	0.136	0.170	0.201
	0.011	0.010	0.010	0.011	0.011	0.010	0.010	0.010	0.007	0.008	0.010	0.008	0.008	0.008	0.011	0.010
	0.342	0.394	0.397	0.367	0.318	0.459	0.416	0.367	0.413	0.464	0.491	0.597	0.577	0.691	0.530	0.516
Umbria	0.068	0.065	0.076	0.067	0.079	0.053	0.074	0.070	0.063	0.047	0.081	0.082	0.088	0.088	0.118	0.065
	0.015	0.015	0.017	0.018	0.015	0.012	0.015	0.014	0.010	0.008	0.012	0.011	0.010	0.011	0.018	0.010
	0.602	0.540	0.527	0.510	0.564	0.566	0.587	0.587	0.653	0.684	0.621	0.649	0.581	0.629	0.631	0.591
Veneto	0.087	0.098	0.119	0.125	0.112	0.108	0.097	0.088	0.074	0.067	0.081	0.086	0.093	0.077	0.073	0.061
	0.006	0.007	0.008	0.009	0.008	0.007	0.006	0.006	0.006	0.005	0.006	0.007	0.007	0.006	0.006	0.004

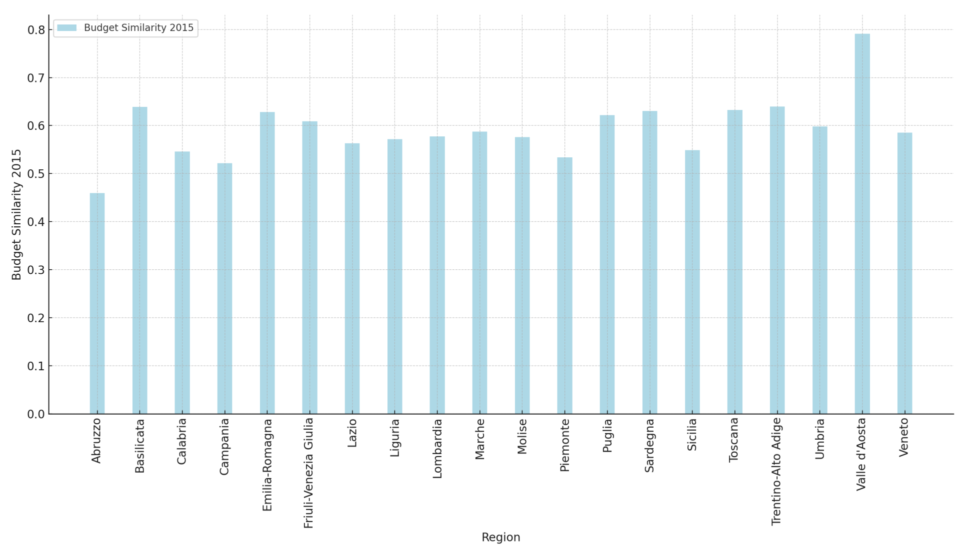
Note: The table displays the average R^2 value, coefficient, and standard error from each of the 5-fold regressions, by region and year. The independent variable is similarity in fiscal policy, and the regressor is similarity in local characteristics.

Figure A.1: Trends in Fiscal Policy Similarity

(a) Time



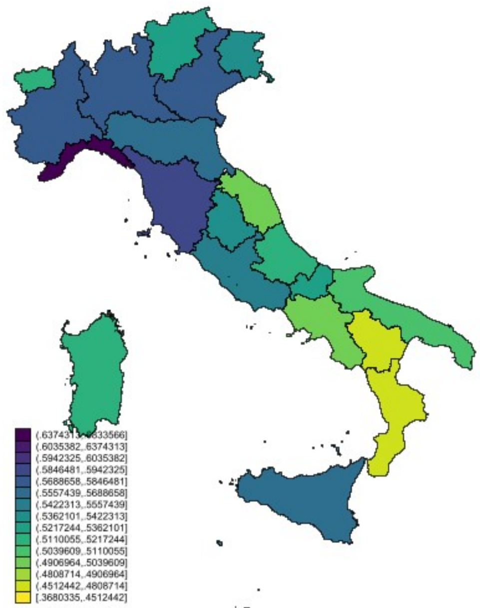
(b) Region



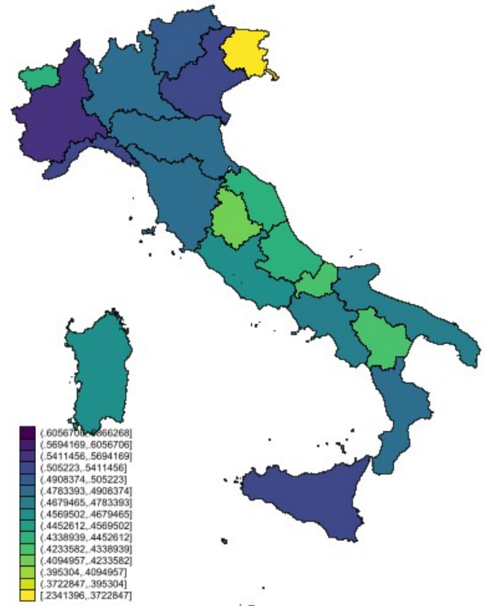
Note: Panel a shows the trend of average budget similarity over the years from 2000 to 2015, while Panel b shows the regional average budget similarity in 2015.

Figure A.2

(a) 2005



(b) 2015



Notes: This figure shows the evolution of fiscal policy divergence from an early period in our timeframe (2005) to ten years later (2015). The measure of fiscal divergence is aggregated at regional level. Darker shades represent higher values of divergence, whereas lighter colors indicate lower levels of divergence.