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Unexpected Fiscal Policies

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JEL Classification: H72, H20, H30

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The prediction errors (residuals) measure fiscal divergence, indicating how much a municipality's behavior deviates from expectations. We apply and test this method using data from Italian municipalities, focusing on how electoral accountability affects policy decision-making. Our findings show that fiscal divergence tends to decrease in the year preceding local elections, illustrating the impact of electoral cycles on political behavior and providing a practical application of the method.

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Unexpected Fiscal Policies*

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Abstract

In this paper, we introduce a method to quantify the deviation of local policymaking from expected norms based on local characteristics. We begin by computing the cosine similarity of municipal public budgets between pairs of municipalities to generate a measure of similarity in policymaking. This measure strongly correlates with differences in local characteristics, such as geographical distance, size and demographic composition, and the political traits of local officials. Next, we use a fixed-effect model of municipality pairs to predict, out-of-sample, their budget similarity based on local characteristics. The prediction errors (residuals) measure fiscal divergence, indicating how much a municipality's behavior deviates from expectations. We apply and test this method using data from Italian municipalities, focusing on how electoral accountability affects policy decision-making. Our findings show that fiscal divergence tends to decrease in the year preceding local elections, illustrating the impact of electoral cycles on political behavior and providing a practical application of the method.

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1. Introduction

Fiscal policy is a critical tool for local governments, shaping their ability to deliver essential services and foster 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 aligns 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 based on its characteristics and compare it to the budget allocations of other jurisdictions with alike 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. Whether this deviation is desirable or not cannot be determined in advance and may depend on the context; for instance, deviation could be related to innovative policy (Bernecker, Boyer and Gathmann, 2021), but also to mismanagement or corruption (Bandiera, Prat and Valletti, 2009). After generating this measure, we investigate how political incentives influence policy divergence. Whether one should expect convergence or divergence in the presence of political incentives depends on the theoretical model under consideration, thus making it an empirical matter.

Our analysis focuses on detailed public budget data and socio-demographic characteristics of 8,000 Italian municipalities from 2000 to 2015. Public budgets are often used as proxies for government policy, reflecting policy-makers' priorities through the size, composition, and revenue sources of budgets. However, traditional research typically examines only a few budget components, limiting the understanding of government decisions. Our first contribution is to adopt techniques commonly used in applied machine learning to analyze the entire budget structure, thereby generating a comprehensive measure of policy similarity. Specifically, we use nearly 4,500 variables representing different parts of the budget and treat these budgets as vectors. By calculating the cosine similarity between these budget vectors for each pair of municipalities within a given region, we can measure how similar their fiscal policies are. A higher cosine similarity indicates that the two municipalities have more similar fiscal policies. A validation exercise shows that our measure correlates with various geographical, socio-demographic, and political characteristics of municipalities. For instance, municipalities that are geographically closer, have similar population sizes, and have a mayor of the same political party have higher cosine similarity values, indicating similar budgets. The age structure of the population is the strongest predictor, while political characteristics like the age and gender of the mayor show a weak correlation with budget similarity, suggesting that these factors have a limited impact on municipal budgets.

Next, we quantify the deviation of local budgets from expected norms based on local characteristics. To achieve this, we estimate a fixed effects model for each region-year with municipalities as fixed effects and perform 5-fold cross-validation to generate predictions. In this model, our policy similarity index is regressed on a variable measuring similarity in many municipal characteristics. The model achieves, on average, an out-of-sample R-squared of 0.536, indicating it captures substantial variation. Additionally, we show a strong correlation between the predicted similarity rankings and the actual similarity values, validating the accuracy of our model's predictions. To estimate the fiscal divergence of each municipality's budget, we use the prediction errors, or residuals, of our trained model. These residuals indicate how much a municipality's budget deviates from what is expected based on its local characteristics and the behavior of other municipalities with similar characteristics. In other words, a high residual suggests that a municipality is implementing policies that differ significantly from those of similar municipalities.

Finally, we test this measure with an empirical application in the context of the political budget cycle to verify its association with political incentives. Political incentives are crucial because politicians tend to adjust their actions based on the electoral cycle, behaving differently when elections are near compared to when they are distant. We test this theory using our measure of fiscal divergence, assessing whether deviations in budget policies change with the timing of electoral cycles. Exploiting the staggered timing of local Italian elections, we show that fiscal divergence decreases as elections approach, suggesting that politicians align their policies more closely with what is expected given their constituents' characteristics. Our results are consistent with a model in which voters have clear preferences regarding government spending and look at budget allocation as a proxy for what politicians care about. Therefore, politicians may favor a composition of the budget that is more in line with what are the priorities of their constituents when facing elections (Drazen and Eslava, 2010).

This paper primarily complements the body of literature examining fiscal policy and its driving factors. These factors 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, 2021; Grembi, Nannicini and Troiano, 2016); electoral rules and term limits (Gagliarducci and Nannicini, 2013); and monetary incentives (Ferraz and Finan, 2009).

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; 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, 2021) 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).

Overall, we provide a novel contribution by applying cosine similarity to local budgets, allowing us to consider the full range of budget decisions—an approach not previously undertaken. This methodology enables us to estimate a new measure of policy divergence by creating a benchmark for budget decisions based on the socio-demographic characteristics of each municipality. This benchmark allows us to analyze divergence, an outcome that was previously difficult to study due to the lack of a robust reference point. Furthermore, we demonstrate that politicians tend to align their behavior with their constituents' characteristics as elections approach but diverge from these expectations when elections are farther away.

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 metrics. 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. Unlike previous studies that typically focused on macro-categories of revenue and expenditure, our dataset includes detailed information on the complete composition of budgets. The Italian local budgets are divided into sections (*quadri*). We use data on revenue (*quadro 2*) and expenditure (*quadri 4* and *5*). 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

[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.

indicators, environmental and urban quality, and demographic and migration dynamics. The complete list of these variables is presented in Appendix Table A.1.

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.

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 metrics 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 population size 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 metrics 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 $\mathbf{A}$ and $\mathbf{B}$ 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).[2]

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

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

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

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. In this approach, each component is treated with equal weight, implying that all elements contribute equally to the overall similarity measure, regardless of their actual significance in the policymaking process.

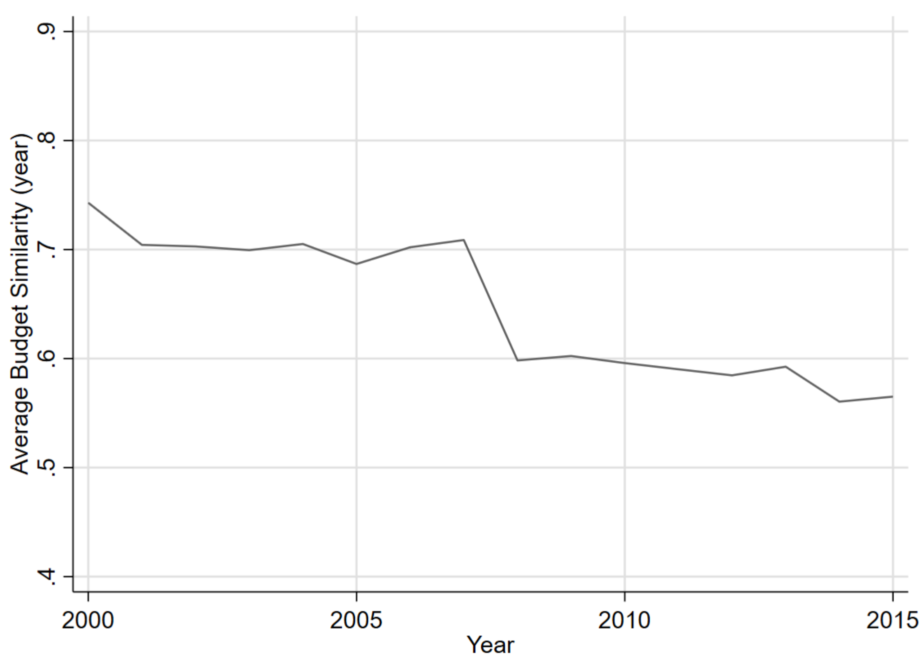
3.2. Generating the Similarity Measures

To generate similarities in policymaking, we analyze the complete structure of the budgets. For the purposes of similarity computation, we excluded from the budget structure all variables with missing values for all municipalities in a given year. The number of components differs across all years; Table A.2 offers a detailed overview of the final number of budget variables employed in each year. Overall, we have more detailed information on the expenditure side rather than the revenue side. We can see an important increase in the number of expenditure features in the year 2008. This variation in budgetary components is important to keep in mind, as it entails that the generated similarity measure primarily offers a cross-sectional interpretation of policy similarity. Primarily for computational reasons, we will generate similarity measures only for pairs of municipalities within the same region and for a given year.

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 Table A.1). Similar to the previous exercise, each variable is treated as a vector component that represents a municipality's socio-demographic characterization. In this case, we standardized the variables by region.

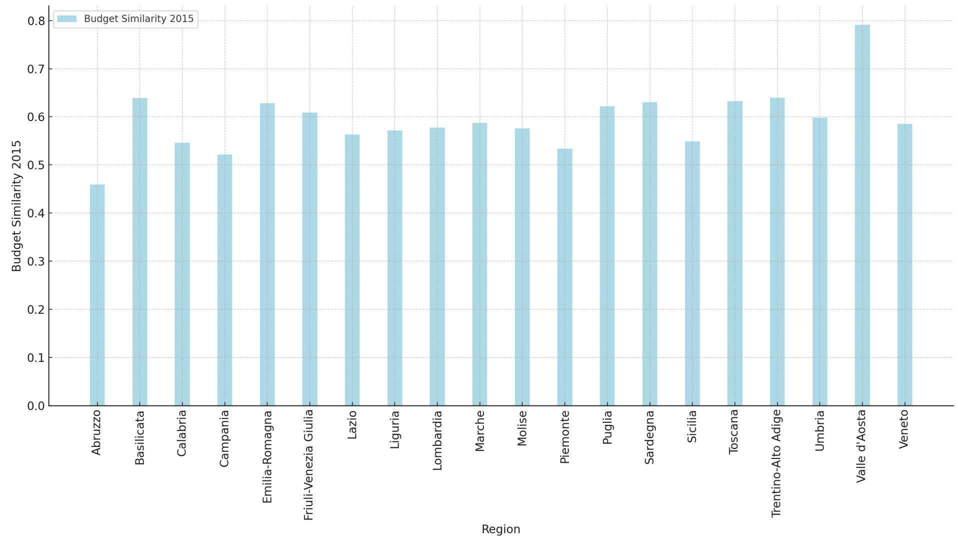
We provide some simple descriptive results in Figures 1 and 2. Figure 1 shows the trend of average budget similarity over the years from 2000 to 2015. The data reveal a relatively stable pattern of similarity until 2008, followed by a noticeable decline. Such a drop is likely due to a change in the budget 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 2 shows the average budget similarity collapsed over the period 2000-2015 for every Italian region. Average budget similarity ranges from approximately 0.45 to almost 0.8, with most regions being within the range of 0.55 to 0.65. There is however some heterogeneity across the regions, with Valle d'Aosta having the highest similarity score (roughly at 0.8) and Abruzzo being the region with the lowest average similarity with approximately 0.45.

Figure 1: Trends in Fiscal Policy Similarity



Note: This figure shows the trend of average budget similarity over the years from 2000 to 2015.

Figure 2: Regional Differences in Fiscal Policy Similarity



Note: This figure shows the regional average budget similarity in 2015.

3.3. A validation exercise

In this section, we provide evidence to support the validity of our measure of policy-making similarity by analyzing how it correlates with the similarity in socio-demographic and political characteristics that are 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.

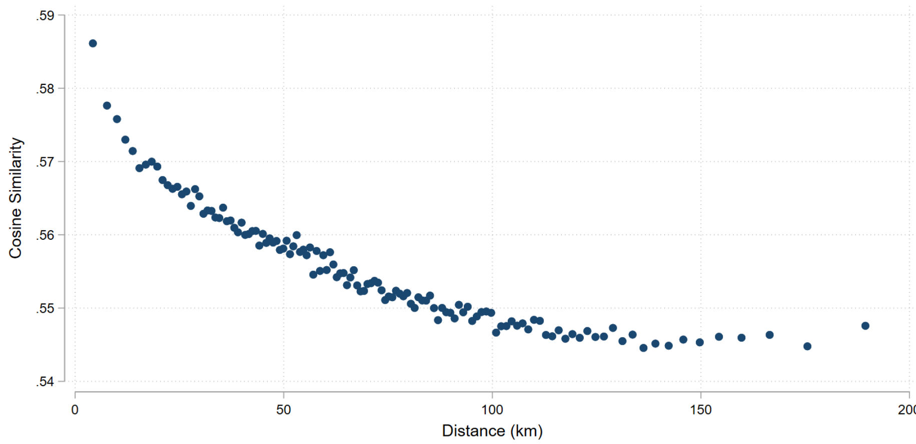
We begin our analysis by examining the relationship between the cosine similarity index and geographical distance, a critical factor discussed in public finance literature. Figure 3 presents a binscatter plot that illustrates a negative correlation between budget similarity and the distance between pairs of municipalities. This finding supports the hypothesis that geographical proximity influences budgetary decisions. Municipalities that are further apart tend to exhibit greater differences in other characteristics, which is also highlighted 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

Figure 3: Binscatter Budget Similarity vs Geographical Distance



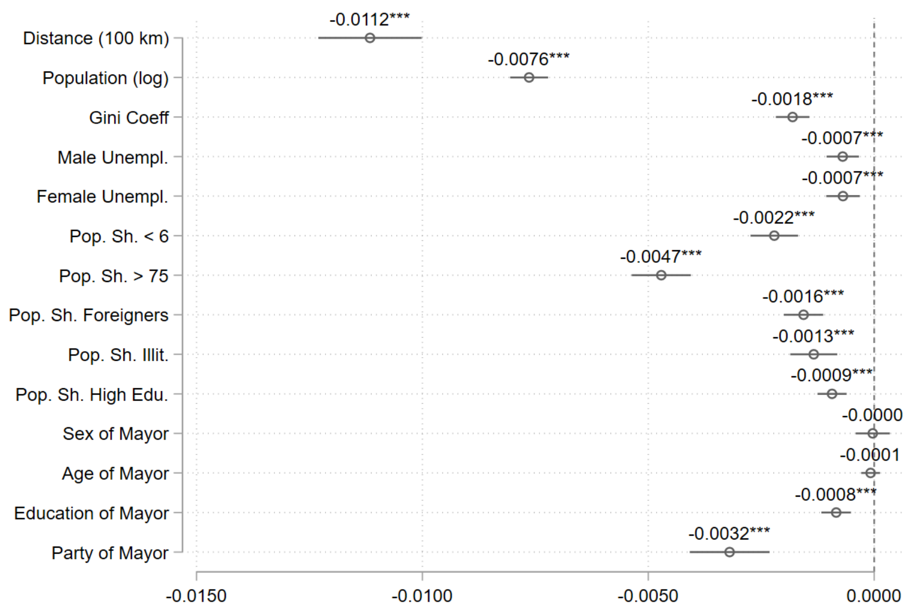
Note: The binscatter plot illustrates the relationship between cosine similarity of municipal budgets and geographical distance between municipalities. Each point represents an aggregated average of budget similarity and distance in kilometers by municipalities.

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, 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.[3] For our exercise, we focus only on the year 2011, which is a population census year.

We present our results graphically in Figure 4. 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

[3]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).

Figure 4: 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.

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. Fiscal Divergence

In this section, we introduce and describe our measure of fiscal divergence. Our approach is grounded in the principle that municipalities with similar characteristics should exhibit similar fiscal behaviors. A deviation from the average behavior of comparable municipalities can, therefore, be interpreted as a divergence in policymaking. This measure allows us to quantify how much a municipality's fiscal decisions differ from those of its similar peers. The presence of fiscal divergence can be interpreted in various ways, and whether such divergence is inherently positive or negative cannot be determined in advance, but it is likely to depend on the specific context. In some cases, divergence may indicate innovative policymaking (Bernecker, Boyer and Gathmann, 2021), while in others, it might reflect inefficiencies or deviations from best practices (Bandiera, Prat and Valletti, 2009). While this paper primarily focuses on measuring and analyzing fiscal divergence, we acknowledge the importance of understanding its underlying causes.

We argue that one way to assess fiscal divergence is by estimating/training a model that accurately predicts similarity in policymaking based on the similarity in local characteristics. From the results of such a model, we can quantify the expected fiscal behaviors of municipalities with similar socioeconomic profiles and identify instances of divergence.

To achieve this, we move beyond the validation exercise of the previous section and use a more detailed representation of differences in local characteristics. This involves using the similarity index in local characteristics discussed in section 3.1, 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 (3.3). 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.

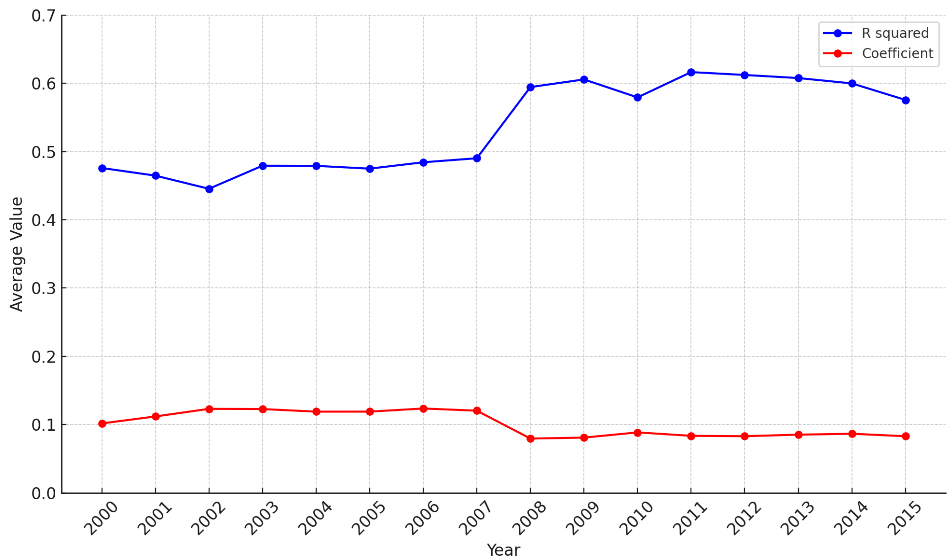
As we are interested in assessing the quality of the predictive power of the model, besides the actual estimation of β, we use a cross-validation approach where the dataset is divided into five folds. Iteratively, we hold out one fold as the test set and train our model on the remaining four folds, which 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 5. The results demonstrate variability over time (Figure 5 Panel a) and across different regions (Figure 5 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.

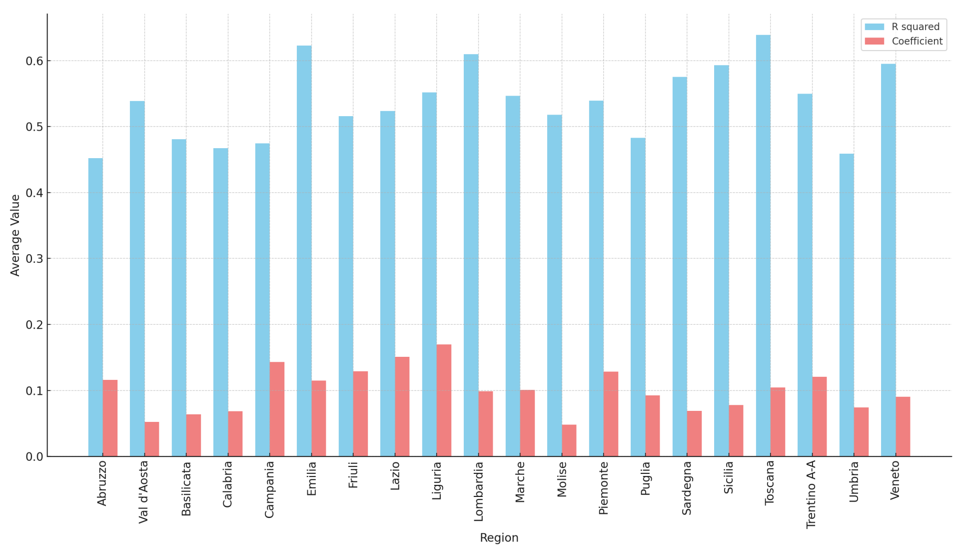
A crucial feature of our estimated model is that if we rank the pairs of municipali-

Figure 5: R-squared and Coefficients - Time and Geographical Variation

(a) Time



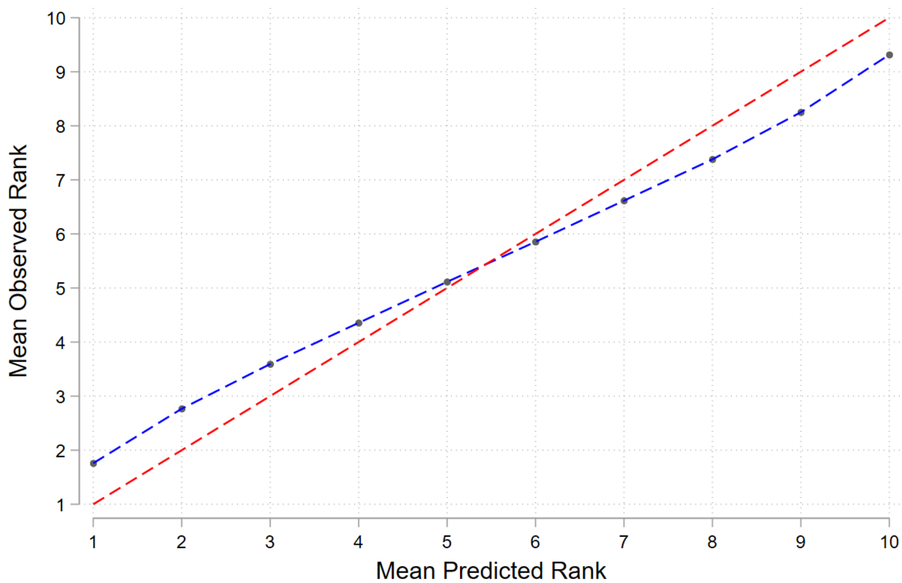
(b) Region



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.

ties based on the outcome variable—specifically, policymaking similarity—this ranking closely aligns with the ranking obtained using the predicted outcome variable. We confirm this using a calibration plot, as shown in Figure 6.

Figure 6: 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.

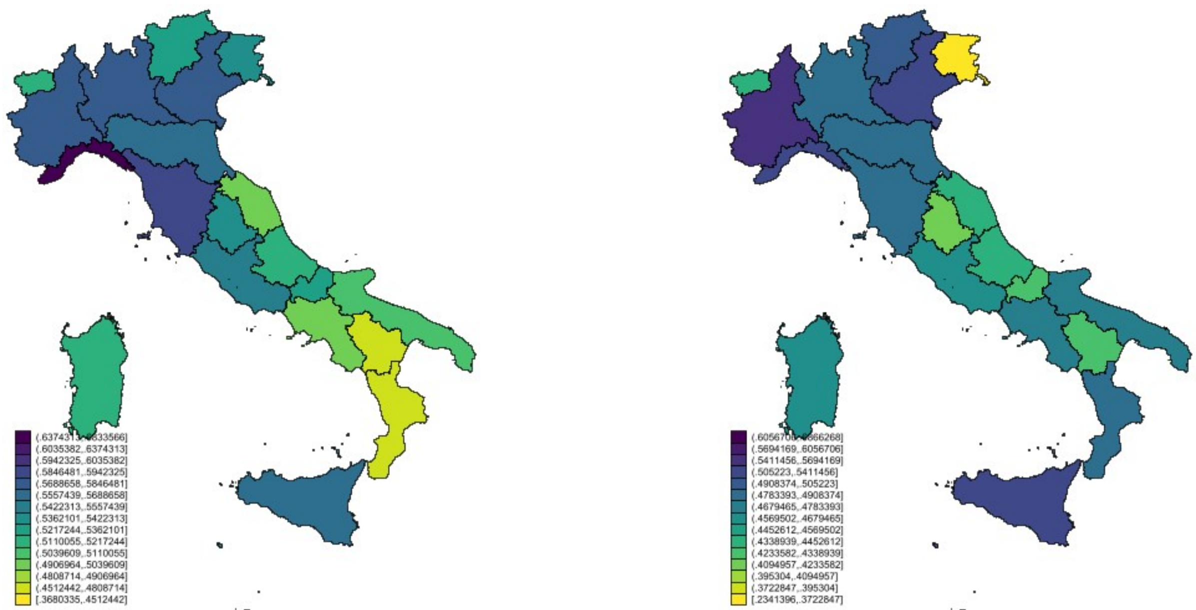
Having validated the quality of the model, we now move to assess the potential deviation in policymaking by looking at the errors/residuals of the model. Therefore, we compute the difference between the observed and predicted value from the model $r_i = y_i - x_i\hat{\beta}$. In other words, the residuals 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.

Figure 7 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.

In the next section we show an application of the fiscal divergence measure in the context of the political budget cycle.

Figure 7

(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.

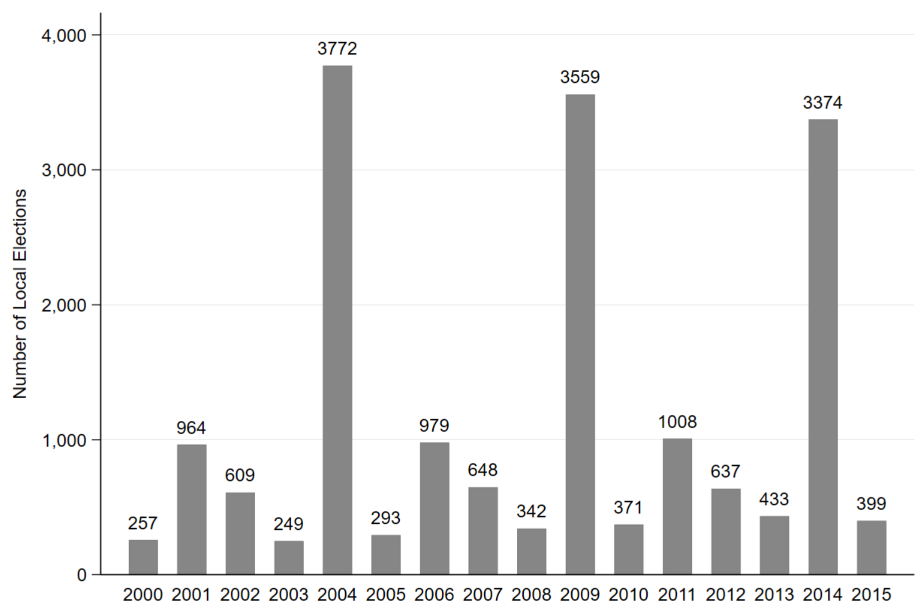
5. Divergence and the Political Budget Cycle

We use the divergence measure to investigate how the strategic fiscal behavior of municipalities responds to 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.

The analysis uses the staggered election schedules of over 8,000 Italian municipalities. The staggered timing results from historical factors and instances where government crises led to the premature end of electoral mandates before their scheduled deadline. As suggested by previous research exploring these features of the Italian local political system, the exogenous timing helps to separate the impact of the electoral cycle from the effects of events occurring in a given year itself and other confounders (Repetto, 2018). Figure 8 shows the number of elections by year.

Figure 8: Number of Municipal Elections by Year



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

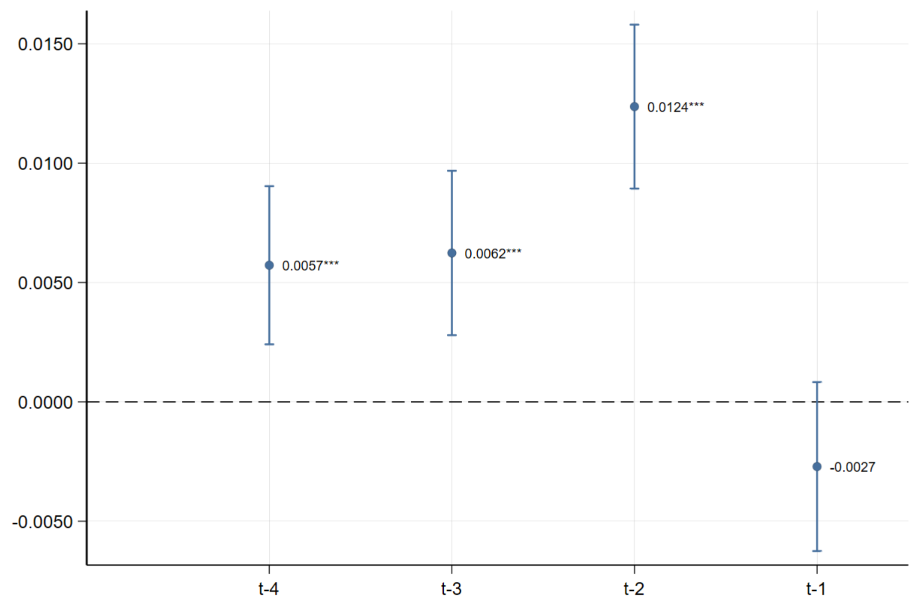
Formally, we estimate the following equation:

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

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 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.[4]

Figure 9: Political Incentives and Fiscal Divergence



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

Our main results are illustrated in Figure 9, 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 more closely with 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 Eslava (2010).

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

6. Conclusion

In this paper, we have introduced a novel approach to evaluating fiscal policy by analyzing government performance across jurisdictions with similar socio-demographic compositions. Our method uses the complete budget structure of municipalities, applying techniques commonnly used to study high-dimensional data, to measure policy similarity. By calculating the cosine similarity between budget vectors for each pair of municipalities, we generated a new metrics that captures fiscal policy decisions going beyond traditional approaches.

Our analysis covered detailed public budget data and socio-demographic characteristics of 8,000 Italian municipalities from 2000 to 2015. We validated our policy similarity measure by showing a strong correlation with different geographical, socio-demographic, and political characteristics of municipalities, confirming that municipalities with similar features tend to exhibit more similar fiscal policies. We then quantified fiscal divergence by estimating a model that predicts policy similarity based on local characteristics. The residuals from this model serve as an indicator of how much a municipality's budget deviates from the expected norms based on its characteristics and those of similar municipalities. This measure of divergence, or fiscal divergence index, provides a robust benchmark for assessing unexpected policy actions.

In an empirical application, we explored the relationship between fiscal divergence and political incentives, particularly focusing on the political budget cycle. Our findings revealed that fiscal divergence decreases as elections approach, indicating that politicians align their policies more closely with the expected preferences of their constituents in the year preceding the election. This behavior supports the theory that politicians adjust their spending priorities to signal alignment with voter interests, particularly in the context of upcoming elections.

Overall, our work contributes to the literature on fiscal policy by providing a new measure of policy divergence and demonstrating its usefulness in understanding the impact of political incentives on fiscal decisions.

Future research could expand on this work by exploring the implications of fiscal divergence in different political and economic environments, as well as investigating the role of other factors, such as media exposure, in shaping local fiscal policies.

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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 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
Abruzzo	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
	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
Val d'Aosta	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
	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
Basilicata	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
	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
Calabria	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
	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
Campania	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
	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
Emilia	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
	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
Friuli	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
	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
Lazio	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
	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
Liguria	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
	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
Lombardia	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
	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
Marche	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
	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
Molise	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
	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
Piemonte	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
	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
Puglia	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
	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
Sardegna	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
	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
Sicilia	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
	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
Toscana	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
	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
Trentino A-A	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
	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
Umbria	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
	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
Veneto	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
	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.