**The Causal Effect of Re-Election Incentives on Corruption: Econometric Analysis Using Brazilian Data**

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## **1. Introduction**

In economics, the study of political corruption is an important and well-researched topic. As politicians are entrusted with control of public finances and positions of influence, the abuse of power by politicians through rent-seeking and corruption threatens many modern democracies. In theory, electoral rules keep politicians accountable and constrain the behavior of corrupt politicians, as voters have the power to oust corrupt politicians from office. While there are convincing theoretical arguments for why political institutions affect corruption, the empirical evidence identifying the specific electoral structures that discipline politicians’ behavior is more limited.

Thus, this study investigates the causal effect of re-election incentives on corruption levels in Brazilian municipalities, with the hypothesis that mayors in their first term, who face re-election incentives, are less likely to engage in corruption compared to second-term mayors, who lack such incentives.

The report will be structured as follows: an introduction providing background on the context of Brazilian municipal politics and corruption; a detailed methodology section outlining the data sources and analytical approach; a results section presenting the findings; a discussion analyzing the implications of these results for electoral accountability and corruption reduction; and a conclusion that summarizes key insights and suggests potential policy recommendations.

## **2. Background**

### **2.1 Literature Review**

Until the 1980s, scholarly research on corruption was largely confined to sociology, political science, history, public administration, and criminal law.[[1]](#footnote-0) Since then, economists have also turned their interest to this topic, largely on account of its increasingly evident link to economic performance. Corruption was often modeled using principal-agent theory, where the "principal" is the electorate, and the "agent" is the politician or government official. The model explores how the separation between the principal (voters) and agent (politicians) leads to moral hazard, where the agent may engage in corrupt behavior if the monitoring and incentive structures are weak.[[2]](#footnote-1)

Much early research focused on weaknesses in public institutions and distortions in economic policies that gave rise to rent-seeking corrupt practices by public officials , with early theoretical work having convincing arguments for why political institutions affect corruption. Myerson theorised that political institutions shaped the incentives of politicians, influencing the likelihood of corruption.[[3]](#footnote-2) In political systems where political leaders face strong electoral accountability and competitive elections, the threat of losing office reduces the incentive to engage in corrupt practices. Similarly, Persson, Roland, and Tabellini argue that in systems where individual legislators are accountable to voters, such as majoritarian systems, the electorate can directly punish corrupt behavior, which leads to more disciplined politicians.[[4]](#footnote-3)

In democratic governing institutions, one crucial component is electoral accountability. Ideally, it works through retrospective voting, where voters reward good performance and punish bad performance on election day, incentivizing politicians to perform well and to be responsive to voters’ wishes. However, the empirical research concerning to what extent voters reward or punish their elected representatives based on their performance was for a long time dominated by economic issues, i.e. the voters’ material well-being and how well the economy was (perceived) to be handled by the incumbents.[[5]](#footnote-4) Even though a few early studies focused on corruption, it was not until about 10 to 12 years ago that the “corruption voting” literature took off. As late as 2013, De Sousa and Moriconi in a review article wrote that “[t]he literature on electoral punishment of corruption is still scarce”.

A significant challenge is that well-functioning electoral accountability processes puts high demands on the electorate. In order to make a well-informed choice, voters must be knowledgeable, be able to correctly assess the personal consequences of the government’s policies, as well as those for society at large, and, finally, be able to distinguish between outcomes that the government can reasonably be held responsible for and those that it cannot. It is therefore not surprising that scholars disagree on the extent to which electoral accountability practically works and leads to reducing corruption.

Many studies employ field experiments or use real-world electoral data to consistently find that politicians involved in corruption scandals lose support and to determine the extent to which corrupt politicians are punished. Much fewer studies examine the inverse, exploring the direct effects of elective electoral accountability on corruption overall.[[6]](#footnote-5) Most studies that treat electoral accountability as the independent variable focus on different aspects of the electoral system (as a proxy) and correlate them with the level of corruption. In a seminal and widely cited study, Persson, Tabellini, and Trebbi (2003) show that certain aspects of the electoral system, such as open lists under proportional representation systems and majoritarian systems in general, positively relate to less corruption. The implicit assumption is that the incentive structures actually work and deter officeholders from engaging in corruption or facilitate the replacement of corrupt politicians with non-corrupt ones.

### **2.2 Problem Background**

The issue of political corruption has long been a significant concern in Brazil, where the relationship between political incentives and corrupt behavior remains a critical area of study. A pivotal moment in the country’s political landscape occurred in 1997, when a constitutional amendment was enacted, allowing mayors to serve a maximum of two consecutive terms.

Additionally, in 2003, the Brazilian government introduced a groundbreaking anti-corruption audit program aimed at increasing transparency and monitoring the use of public funds at the municipal level. The program's goal was to deter corrupt practices by providing external scrutiny of public administration. This initiative allowed for the systematic collection of data on corruption levels across various municipalities, creating a unique opportunity to assess the relationship between political incentives and corruption.

The dataset under examination includes audit data from 496 municipalities, which were randomly selected through a lottery system. These municipalities represent a diverse range of local governments, each subjected to audits designed to identify instances of corruption during the 2001–2004 electoral term. The data provides a unique opportunity to objectively measure corruption levels, ensuring a more accurate understanding of the dynamics between political incentives and corrupt behavior.

## **3. Data Description**

For our data, we use the dataset "corruptiondata.dta" with variables on corruption outcomes, mayoral characteristics, municipal features, and political/judicial controls. Specifically, our measures of corruption were:

1. Share of audited resources found to involve corruption (**pcorrupt**).
2. Share of audited items involving corruption (**ncorrupt\_os**).
3. Log of total number of corruption irregularities (**log\_valor\_corrupt**).

For our Treatment Variable, we used the ‘first’ binary variable as an indicator for whether the mayor is in their **first term** (our treatment group) or their **second term** (our control group).

In addition, we sorted our covariates into four categories: Mayoral, Municipal, Judicial and Political, and Dummy variables (e.g., state and lottery dummies). We used these covariates as robustness checks to ensure that our estimation of the average treatment effect was robust to introduction of additional controls.

## **4. Methodology**

### **4.1 Identification Strategy**

To estimate the effect of re-election incentives on the level of political corruption in a municipality, the ideal experiment would be to randomly assign the possibility of re-election across municipalities and then measure the differences in corruption levels across these two groups of municipalities among mayors in their first term of office. However, in practice such an experimental design is not possible.

Instead, given the data available, our identification strategy is a fuzzy regression discontinuity design, where this strategy takes advantage of the term limit rule, where mayors in their first term (treatment group) and second term (control group) are treated differently based on their re-election incentives.

By comparing the behavior of mayors at the cutoff (first-term vs. second-term) while controlling for other characteristics, this method allows for the estimation of the causal effect of re-election incentives on corruption, with a focus on the term limit as a source of variation. We consider this strategy "fuzzy" because not all mayors in the second term are necessarily unaffected by re-election incentives (e.g., if they plan to run for a different office or are not restricted by the term limit). In the data, we use variation only from municipalities audited at the same time and in the same state, while controlling for a full set of mayor and municipal characteristics.

To estimate the causal effect, we use debiased machine learning (DML). We believe DML is applicable here because it provides estimators of nuisance parameters when these parameters are highly complex. We believe that the relationship between the covariates and the outcome to be both non-linear and high-dimensional.

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### **4.2 Empirical estimation strategy**

Our estimation strategy follows two treatment strategies based on the general framework for estimating and doing inference about the low dimensional parameter in the presence of a high dimensional nuisance parameter.

In our first set of models, we assume that there is a homogenous treatment effect. Specifically, we assume that the outcome variable is related to the treatment by a partially linear model:

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Where:

1. Y is the outcome variable, which will be a measure of corruption. This will be varied to check for robustness
2. X: a vector of covariates, which are split into categories and then added in successive models to check for robustness. These categories include mayoral characteristics, municipal characteristics, political and judicial covariates, and lastly dummy covariates.
3. D: our treatment variable that indicates whether the mayor is in his first term
4. : our parameter of interest
5. U: unobserved municipal and mayor characteristics that determine corruption

To create a doubly robust moment for the partially linear model, we estimate under the following model by regressing W on V:



Where:

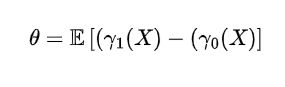
1. is the machine learning model’s prediction of the level of corruption conditional on a set of covariates and without conditioning on the treatment.
2. is the estimated propensity score derived by applying a logistic regression of D on X.

In our second set of models, we assume that there is a heterogeneous treatment effect. There are a few reasons to posit that the effect of re-election incentives on the level of corruption may vary. First, mayors with stronger career ambitions may behave differently even in the presence of no re-election incentives for his current office. A second-term mayor with a long-term political career in mind may be more cautious and less likely to engage in corrupt activities, as the cost of being caught could outweigh short-term gains. By contrast, a second-term mayor who plans to leave office or pursue other opportunities may have less incentive to maintain a clean record.

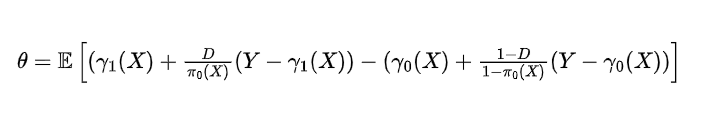
Secondly, the history of corruption and political environment in different municipalities may affect how re-election incentives translate into behavior. In municipalities where political corruption is more entrenched, the effect of re-election incentives on corruption might be weaker as voters either do not view this behavior as abnormal or may believe that the incumbent's political rivals will do better.

Thirdly, in larger municipalities with more complex governance structures, re-election incentives might have less of an impact on individual behavior because the mayor may feel less directly accountable for corruption. Conversely, in smaller municipalities where the mayor has more direct control over local resources, the effect of re-election incentives on corruption might be more pronounced.

Thus, mayoral, political and municipal covariates could all play a role in the treatment effect. Therefore, we model a heterogeneous treatment effect under the following model:



To create a doubly robust moment for the partially linear model, we estimate under the following model:



Where:

1. is the machine learning model’s prediction of the level of corruption conditional on a set of covariates and the presence of being in the first-term.
2. is the machine learning model’s prediction of the level of corruption conditional on a set of covariates and the absence of being in the first-term.

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### **4.3 Machine Learning Models used**

To estimate treatment effects under both homogeneous and heterogeneous assumptions, we use a combination of machine learning methods.

We selected Lasso for its ability to handle high-dimensional data and perform feature selection using L1 regularization. It was used in estimating both the propensity scores (E[D|X]) and the outcome models (E[Y|X]) under the assumption of linear relationships. We believe that Lasso is particularly useful when introducing all of the covariates as it helps avoid overfitting by controlling the complexity of the model and results in sparse solutions.

We also selected Random Forest as it combines multiple decision trees to capture non-linearities and complex interactions in the data. It is particularly robust to overfitting due to the bootstrapping and aggregation (bagging) process.

We initially selected Neural Network but instead chose to specifically use MLP due to the observation that the dataset isn’t extremely complex. As NN does not tend to outperform kernelized linear regressions when complexity is moderate, it’s reasonable for us to use MLP to save computational difficulties. We used a 3-layer architecture (128-64-32 neurons), which is normally used for moderate datasets that ensures a balance between model flexibility and computational efficiency. MLP was chosen for its ability to capture non-linear relationships and interactions in structured/tabular data, and it is expected to outperform general neural networks in this setting.

Lastly, we applied Gradient Boosting for its effectiveness in capturing subtle patterns in the data, making it well-suited for heterogeneous treatment effects where interactions between covariates and treatment status are expected to be complex in this dataset.

For all the machine learning methods training process, we used debiased ML and 5-fold cross-fitting to ensure robustness and out-of-sample predictions. The number of layers is decided considering the balance between computational complexity and robustness.

### **4.4 Balance Checks**

Additionally, we consider the effect of trimming propensity scores to focus on the most relevant observations for estimating causal effects. We only included observations with an estimated propensity score between 0.01 and 0.99, as trimming the propensity scores ensures that the treatment and control groups are more comparable.

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## **5. Findings:**

### **5.1 Causal Estimates**

This section provides evidence that municipalities where mayors face re-election incentives are associated with significantly lower levels of corruption, as measured by the share of stolen resources. These findings are robust to alternative definitions of corruption, as well as to various specifications and estimation techniques.

Table 1 presents results from estimating several machine learning variants to the heterogenous treatment effect model, where the dependent variable is the share of audited resources that involve corruption. Column 1 reports the unadjusted relationship between whether the mayor is in his first term and the share of stolen funds. The remaining columns correspond to specifications that include additional sets of controls. The specifications presented in columns 2-4 account for various mayors, demographic and institutional characteristics of the municipality.

As indicated by the negative theta produced by all ML Methods, we would expect a **negative** treatment effect between “being in the first term” and the share of audited resources that involved corruption for Brazil mayors in 2001-2004 term. In other words, there is a negative causal relationship between reelection incentive and corruption.

We find that this negative relationship holds even for other measures of corruption, specifically the share of audited items found to involve corruption in Table 2, as well as the number of irregularities associated with corruption in Table 3.

**Model Robustness and Performance Findings:**

In terms of robustness, Lasso and Random Forest consistently improve their performance (lower MSE) as more covariates are added, both under heterogeneous and homogeneous assumptions. This indicates their ability to leverage richer information while maintaining stability. MLP and Gradient Boosting exhibit instability with fewer covariates, likely due to overfitting and complexity in capturing relationships. Overall, as more covariates are included, all models show reduced variability, although the extent of improvement varies.

In terms of ML performance, Lasso consistently produces robust and precise results across all outcomes and covariates. Random Forest also performs well but has slightly higher variability compared to Lasso. MLP struggles with instability and large MSEs, particularly with limited covariates. Gradient Boosting produces reasonable estimates but suffers from higher MSEs, reflecting weaker precision.

For **pcorrupt** and **ncorrupt\_os**, Lasso, Random Forest, and Gradient Boosting produce similar treatment effect estimates when all covariates are included (Covariates\_4). The minor deviations between them suggest that the results are robust across these models. However, the estimate from MLP shows a greater discrepancy, likely due to its limited architecture (limited layers) or overfitting to noise.

For **log\_valor\_corrupt**, Lasso, Random Forest, and MLP converge on similar treatment effect estimates. In contrast, Gradient Boosting produces a significantly lower treatment effect estimate alongside high MSE (231) under the heterogeneous assumption. This deviation indicates weaker precision and highlights the model's sensitivity to complex or noisy relationships in the data.

The similarity in treatment effect estimates when all covariates are included demonstrate that the overall robustness of the models is at a reasonable level. Lasso stands out as the most consistent and precise method, while Random Forest gives competitive performance with slightly higher variability. Gradient Boosting, though capable of reasonable estimates, struggles with precision under certain conditions, particularly for complex or noisy outcomes. MLP exhibits the greatest instability, indicating a need for deeper architecture or improved regularization.

**Homogenous vs. Heterogeneous**:

Comparing the values from Homogenous Tables (Table 4-6) and Heterogeneous Tables (Table 1-3), MSE under homogeneous conditions are significantly lower, which suggests that homogeneous data is easier for the models to fit, likely due to fewer complexities or noise in the relationships.

For outcome **pcorrupt** and **log\_valor\_corrupt**, the magnitude of the treatment effect estimates is generally higher under homogeneous conditions compared to heterogeneous settings. For example, In log\_valor\_corrupt, the estimates under homogeneous conditions (Table 6) are larger in magnitude for Lasso (-1.1900), Random Forest (-0.9383), MLP (-1.3067), and Gradient Boosting (-0.8237), compared to their heterogeneous counterparts (Table 3): Lasso ( -1.0675), Random Forest (-0.9759), MLP (-0.7585), and Gradient Boosting (-0.3724). This pattern suggests that under homogeneous assumptions, the models attribute a larger portion of the outcome variation to the treatment effect, which could be due to the absence of unobserved heterogeneity, which simplifies the estimation process and reduces the noise competing with the treatment variable.

For **ncorrupt\_os**, no significant differences in treatment effect estimates are observed between homogeneous and heterogeneous conditions. This might suggest that the relationship between covariates and the outcome is less sensitive to heterogeneity, potentially indicating a simpler or more linear association for this outcome.

Despite the lower MSE under homogeneous conditions, we believe that the heterogeneous assumption is more appropriate for our analysis. Real-world data often contains unobserved heterogeneity due to variations across individuals, groups, or contexts. Ignoring such heterogeneity may oversimplify the relationships and obscure important subgroup-specific treatment effects. By accounting for heterogeneity, we can provide a more realistic representation of the data and improve the generalizability of our findings, ensuring that the models capture the full complexity of the treatment effects across different covariate specifications.

## **6. Conclusion**

In conclusion, our analysis provides strong evidence that re-election incentives significantly reduce corruption among mayors in Brazilian municipalities. Specifically, we find that first-term mayors, who face re-election pressures, are less likely to engage in corrupt practices compared to second-term mayors who do not have these incentives. These results are consistent across multiple corruption measures and estimation techniques, supporting the hypothesis that electoral incentives play a crucial role in curbing corrupt behavior.

Based on our results, Lasso appears to be the most consistent and precise method, delivering stable treatment effect estimates and achieving the lowest MSE across both homogeneous and heterogeneous assumptions.

Among the three outcome variables, pcorrupt stands out as the best-performing outcome variable. The similarity between treatment effect estimates across different models (Lasso, Random Forest, Gradient Boosting) is more pronounced for pcorrupt compared to the other outcomes, indicating greater robustness and reliability. Furthermore, the reasonably low MSE values across covariate specifications suggest that the models are able to fit the pcorrupt outcome variable more effectively, with less variability and higher precision.

However, several avenues for further research remain. Future studies could explore the long-term effects of re-election incentives, particularly how they influence political behavior after mayors transition out of office. Additionally, research could investigate the role of local political culture and institutional factors in shaping the effectiveness of electoral incentives. Expanding the analysis to include different regions or countries with varying political structures may provide a broader understanding of how re-election incentives influence corruption globally. Finally, examining the impact of anti-corruption policies, such as audits or transparency initiatives, on political behavior could offer valuable insights into designing more effective governance systems.

**Appendix 1: Covariate Groupings**

mayor\_covariates = [

"pref\_idade\_tse", # Age

"pref\_masc", # Gender

"pref\_escola", # Schooling

"winmargin2000", # Margin of victory in 2000

"exp\_prefeito" # Was previously a mayor in a consecutive term

“party\_d\*" # Party affiliation

“vereador9600” #indicator if mayor was a legislator during 1996-2000

]

municipal\_covariates = [

"lpop", # Log of population in 2000

"purb", # Percentage of population in urban sectors

"p\_secundario", # Percentage with at least secondary education

"mun\_novo", # New municipality indicator

"lpib02", # Log of GDP per capita in 2002

"gini\_ipea" # Gini coefficient

“media2” #indicator if municipality has a AM radio station and local newspaper

]

political\_judicial\_covariates = [

"ENEP2000", # Effective number of parties in 2000 mayor elections

"ENLP2000", # Effective number of parties in 2000 legislative elections

"p\_cad\_pref" # Proportion of legislators from the same party as the mayor

]

dummy\_covariates = [

uf\_d\* : State dummies

sorteio\* : Lottery dummies

]

**Appendix 2: Results Table (Heterogeneous)**

\* Notation:

Covariates\_1: Includes only mayor characteristics.

Covariates\_2: Including both municipal characteristics and mayor characteristics.

Covariates\_3: Includes mayor, municipal, and political/judicial characteristics.

Covariates\_4: Includes all covariates (mayor, municipal, political/judicial characteristics, and dummy variables).

(#): Corresponding MSE value of the estimate.

Table 1: Heterogeneous with output = pcorrupt

|  | **ML Method** | **Covariates\_1** | **Covariates\_2** | **Covariates\_3** | **Covariates\_4** |
| --- | --- | --- | --- | --- | --- |
| 0 | Lasso | -0.020254 (0.016171) | -0.020004 (0.016512) | -0.021204 (0.016981) | -0.021965 (0.017303) |
| 1 | Random Forest | -0.024551 (0.016579) | -0.018236 (0.016606) | -0.020898 (0.019889) | -0.027213 (0.019589) |
| 2 | Multiple-layer Perceptron | -0.076400 (0.843246) | -0.026985 (0.066140) | -0.054484 (0.372127) | -0.042394 (0.108669) |
| 3 | Gradient Boosting | -0.020351 (0.066814) | -0.019443 (0.058081) | -0.015212 (0.137367) | -0.033108 (0.115371) |

Table 2: Heterogeneous with output = ncorrupt\_os

|  | **ML Method** | **Covariates\_1** | **Covariates\_2** | **Covariates\_3** | **Covariates\_4** |
| --- | --- | --- | --- | --- | --- |
| 0 | Lasso | -0.008128 (0.003728) | -0.006750 (0.003707) | -0.007074 (0.003574) | -0.009060 (0.003216) |
| 1 | Random Forest | -0.009267 (0.003814) | -0.003394 (0.003918) | -0.004831 (0.003618) | -0.007590 (0.002966) |
| 2 | Multiple-layer Perceptron | -0.047969 (4.310269) | -0.015525 (0.026737) | -0.012250 (0.092694) | -0.027418 (0.091531) |
| 3 | Gradient Boosting | -0.006718 (0.014550) | -0.009970 (0.031864) | -0.015407 (0.054797) | -0.010750 (0.014521) |

Table 3: Heterogeneous with output = log\_valor\_corrupt

|  | **ML Method** | **Covariates\_1** | **Covariates\_2** | **Covariates\_3** | **Covariates\_4** |
| --- | --- | --- | --- | --- | --- |
| 0 | Lasso | -0.992246 (39.054955) | -0.905899 (38.035667) | -1.012787 (37.229637) | -1.067526 (36.285240) |
| 1 | Random Forest | -1.013124 (39.744113) | -0.816997 (36.712125) | -0.848086 (39.230805) | -0.975908 (33.768337) |
| 2 | Multiple-layer Perceptron | -1.023083 (105.423218) | 0.489262 (908.862427) | -0.777292 (47.814293) | -0.758514 (63.923859) |
| 3 | Gradient Boosting | -0.193866 (357.192553) | -1.009129 (190.921643) | -0.856813 (506.335021) | -0.372401 (231.858423) |

**Appendix 3: Results Table (Homogeneous)**

Table 4: Homogeneous with output: pcorrupt

|  | **ML Method** | **Covariates\_1** | **Covariates\_2** | **Covariates\_3** | **Covariates\_4** |
| --- | --- | --- | --- | --- | --- |
| 0 | Lasso | -0.017920 (0.010611) | -0.017183 (0.010455) | -0.021765 (0.010458) | -0.023743 (0.010310) |
| 1 | Random Forest | -0.022994 (0.011305) | -0.019338 (0.011028) | -0.019102 (0.011039) | -0.023355 (0.010866) |
| 2 | Multiple-layer Perceptron | -0.031959 (0.017039) | -0.009896 (0.025246) | -0.033487 (0.019224) | -0.014225 (0.034814) |
| 3 | Gradient Boosting | -0.018237 (0.012909) ) | -0.020428 (0.012555) | -0.019965 (0.012114) | -0.019908 (0.012329) |

Table 5: Homogeneous with output = ncorrupt\_os

|  | **ML Method** | **Covariates\_1** | **Covariates\_2** | **Covariates\_3** | **Covariates\_4** |
| --- | --- | --- | --- | --- | --- |
| 0 | Lasso | -0.009267 (0.002861) | -0.006682 (0.002634) | -0.007514 (0.002631) | -0.008505 (0.002078) |
| 1 | Random Forest | -0.009108 (0.002943) | -0.004336 (0.002763) | -0.004482 (0.002717) | -0.007674 (0.002254) |
| 2 | Multiple-layer Perceptron | -0.012347 (0.009806) | -0.018507 (0.014310) | -0.007227 (0.011910) | -0.025236 (0.022335) |
| 3 | Gradient Boosting | -0.009557 (0.003252) | -0.006281 (0.003009) | -0.004934 (0.002953) | -0.006349 (0.002226) |

Table 6: Homogeneous with output = log\_valor\_corrupt

|  | **ML Method** | **Covariates\_1** | **Covariates\_2** | **Covariates\_3** | **Covariates\_4** |
| --- | --- | --- | --- | --- | --- |
| 0 | Lasso | -0.913043 (28.488840) | -0.769087 (26.503841) | -1.001436 (26.460489) | -1.190014 (24.754757) |
| 1 | Random Forest | -0.974373 (29.498879) | -0.773453 (27.397548) | -0.872685 (27.287176) | -0.938316 (25.969169) |
| 2 | Multiple-layer Perceptron | -1.001793 (33.150330) | -0.668360 (28.804699) | -0.514015 (29.386236) | -1.306737 (29.128323) |
| 3 | Gradient Boosting | -1.047505 (33.206817) | -0.804077 (28.994380) | -0.519726 (28.185947) | -0.823704 (28.820632) |

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