

A longitudinal analysis of the degree of accomplishment of anti-corruption measures by Italian municipalities: a latent Markov approach

Analisi longitudinale del grado di attuazione di misure anti-corruzione nei comuni italiani: un approccio latent Markov

Simone Del Sarto, Michela Gnaldi, Francesco Bartolucci

Abstract The recent Italian anti-corruption law has introduced a new figure, the supervisor for corruption prevention, who has to fill in an annual report about the accomplishment of anti-corruption measures within the institution he/she represents. Using data coming from such annual reports referred to a sample of Italian municipalities, a latent Markov model is fitted to investigate the evolution over time of the degree of accomplishment of anti-corruption measures. First results evidence three latent states of increasing virtuosity. Moreover, at the beginning of the study, the most of the sample belongs to the low and intermediate states of virtuosity, even if there is evidence of high probabilities to move to upper states over time.

Abstract *La recente legge anti-corruzione italiana ha introdotto una nuova figura, il responsabile per la prevenzione della corruzione, che deve predisporre una relazione annuale sull'attuazione di misure anti-corruzione in capo all'istituzione che rappresenta. Per analizzare i dati provenienti da tali relazioni annuali riferiti a un campione di comuni italiani, è stato stimato un modello latent Markov, che permette di investigare l'evoluzione temporale del grado di attuazione di misure anti-corruzione. I primi risultati evidenziano l'esistenza di tre stati latenti corrispondenti a gradi crescenti di virtuosità. Inoltre, agli inizi dello studio, la maggior parte del campione appartiene ai primi due stati (bassa e intermedia virtuosità), sebbene vi siano alte probabilità di spostarsi nel tempo in stati corrispondenti a gradi più alti di virtuosità.*

Key words: Corruption prevention, latent Markov, supervisor for corruption prevention

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1 Introduction

The recent approaches to combat corruption have seen a shift from a penal and repressive focus to a broader preventive approach. Attention has to be paid not only on all illegal and criminal conducts, but also on any social behaviour and malpractice, even if it is not framed in a specific type of penal offence against public administration [2].

The Italian legislation has recently adopted such preventive perspective with law n. 190 of 2012, named “Provisions for the prevention and repression of corruption and lawlessness in the public administration”. It introduces two main tools to be implemented within all Italian public administrations, in order to reduce the risk of occurrence of corruptive events. The first is a three-year plan for corruption prevention (PTPC), by which each administration evaluates its own internal situation in terms of exposure levels to the risk of corruption and specifies potential organisational changes to reduce such a risk. The second is the introduction of a new figure, the supervisor for corruption prevention (RPC) that, within the public administrative unit (i.e., regions, municipalities, etc.) he/she represents, fills in an annual report about the degree of accomplishment of anti-corruption measures. This report is based on a questionnaire made available by the Italian National Anticorruption authority (ANAC). Previous works [3, 4, 5] exploited the data contained in the RPC forms for investigating the degree of accomplishment of anti-corruption measures by Italian municipalities, with the aim of ascertaining clusters of units characterised by distinctive anti-corruption behaviours, their geographical distribution, and the association between anti-corruption behaviours and some relevant covariates (e.g., the municipality size).

The objective of the present work is to extend previous findings by deepening our understanding as regards the evolution over time of anti-corruption behaviours of Italian municipalities. A statistical model suitable for the aim at issue is the Latent Markov (LM) model, whose original formulation is due to Wiggins [7]; for an up to date review, see Bartolucci et al. [1]. The LM model is tailored to the analysis of longitudinal dataset, specifically made of several response variables observed at different time occasions for each unit. It allows us to cluster the sample units in latent states as regards the underlying latent variable (degree of accomplishment of anti-corruption measures in our case) and to describe the evolution over time of the transitions among latent states.

The remainder of this work is organised as follows. Section 2 briefly describes the data used for this analysis, while the LM model is introduced in Section 3. Section 4 shows the results, while some concluding remarks are provided in Section 5.

2 The data

The data we consider are collected through the RPC forms for the years from 2014 – the year in which the anti-corruption law entered into force – to 2016. The sample is made of 213 municipalities, comprising all Italian province municipalities, all the other municipalities with at least 40,000 inhabitants and particular “advised” municipalities, as stated by ANAC act n. 71 of 2013.

The objective of the present work is to sketch the evolution over time of the Italian municipalities attitude as regard the degree of implementation of anti-corruption measures. For this reason, we focus on ten questions of the RPC form, requiring the administrations to state whether a specific anti-corruption measure has been accomplished in the reference year. The selected ten questions concern the following subjects:

1. monitoring the sustainability of all measures, general and specific, identified in the PTPC;
2. specific measures, in addition to mandatory ones;
3. computerising the flow to fuel data publication in the “transparent administration” website section;
4. monitoring data publication processes;
5. training of employees, specifically dedicated to prevention of corruption;
6. staff turnover as a risk prevention measure;
7. checking the truthfulness of statements made by parties concerned with unfitness for office causes;
8. measures to verify the existence of incompatibility conditions;
9. prearranged procedures for issuing permits for assignments performance;
10. whistleblowing, which is a procedure for reporting the collection of misconduct by public administration employees.

Three possible answers can be provided to these items, ordered according to their virtuosity: (A) “Yes, the anti-corruption measure has been accomplished” (the most virtuous behaviour); (B) “No, the anti-corruption measure has not been accomplished because it was not expected by the PTPC” (intermediate level of virtuosity); (C) “No, the anti-corruption measure has not been accomplished but it was expected by the PTPC” (the least virtuous conduct).

3 The latent Markov model

Suppose that for every unit we observe the vector of r response variables at occasion $t = 1, \dots, T$, denoted by $\mathbf{Y}^{(t)} = [Y_1^{(t)}, \dots, Y_r^{(t)}]^\top$. Each variable $Y_j^{(t)}$ is categorical with l_j modalities, coded from 0 to $l_j - 1$, $j = 1, \dots, r$. We assume that a latent process $\mathbf{U} = [U^{(1)}, \dots, U^{(T)}]^\top$ affects the response

variables: such a process follows a first-order Markov chain with state space $\{1, \dots, k\}$. Local independence is assumed for the variables in each $\mathbf{Y}^{(t)}$, so its r components are conditionally independent given $U^{(t)}$.

The model at issue has the following parameters:

- $\phi_{jy|u}$: conditional response probability that component $Y_j^{(t)}$ assumes modality y , given latent space u , with $j = 1, \dots, r$, $t = 1, \dots, T$, $y = 0, \dots, l_j - 1$ and $u = 1, \dots, k$;
- π_u : initial probabilities, with $u = 1, \dots, k$;
- $\pi_{u|\bar{u}}^{(t)}$: transition probabilities from state \bar{u} to state u at time t , with $u, \bar{u} = 1, \dots, k$ and $t = 2, \dots, T$.

The model assumptions imply that

$$f_{\mathbf{Y}|\mathbf{U}}(\mathbf{y}|\mathbf{u}) = \prod_{t=1}^T \phi_{\mathbf{y}^{(t)}|u^{(t)}},$$

where \mathbf{Y} is a vector obtained by the union of the vectors $\mathbf{Y}^{(t)}$, $t = 1, \dots, T$ and in general $\phi_{\mathbf{y}|u}$ is the probability that $\mathbf{Y}^{(t)}$ assumes value \mathbf{y} , given latent state u . Moreover, given the local independence assumption, $\phi_{\mathbf{y}|u}$ can be obtained as the product of the single conditional probabilities over the r components, as follows:

$$\phi_{\mathbf{y}|u} = \prod_{j=1}^r \phi_{jy_j|u}.$$

The model parameters are estimated by maximum likelihood through an Expectation-Maximisation algorithm: see [1] for details.

4 Results

According to the Bayesian Information Criterion (BIC) [6], we find evidence of $k = 3$ latent states. By inspecting the conditional response probabilities (see Table 1), it is possible to notice that such states correspond to increasing levels of corruption prevention fulfilment. The estimates of the initial probabilities are reported in Table 2(a). Hence, in 2014 (beginning of the study), the state of the most virtuous municipalities (i.e., those grouped in the third latent state) collects less than 15% of administrations, while the other two states approximately equally split the remaining units.

Regarding the transition probabilities – see Table 2(b) and 2(c) – we note that the probabilities to remain in the current state are higher than those to move to other states and such probabilities are increasing over time. However, from 2014 to 2015 units belonging to the first two states (characterised by low and intermediate virtuosity) have large probability to move to higher state,

hence to increase their compliance of anti-corruption measures. In 2016 the situation seems to stabilise, since almost all the off-diagonal elements of the relative transition matrix are close to 0, expect for a share of probability (around 20-30%) to move to the third state for units belonging to the first two states.

Table 1 Estimates of the conditional response probabilities

| Item 1 | | | | Item 6 | | | |
|----------|-------|-------|-------|----------|-------|-------|-------|
| | State | | | | State | | |
| Response | 1 | 2 | 3 | Response | 1 | 2 | 3 |
| A | 0.526 | 0.866 | 0.929 | A | 0.193 | 0.471 | 0.647 |
| B | 0.126 | 0.022 | 0.022 | B | 0.253 | 0.156 | 0.131 |
| C | 0.348 | 0.111 | 0.049 | C | 0.554 | 0.373 | 0.222 |

| Item 2 | | | | Item 7 | | | |
|----------|-------|-------|-------|----------|-------|-------|-------|
| | State | | | | State | | |
| Response | 1 | 2 | 3 | Response | 1 | 2 | 3 |
| A | 0.332 | 0.792 | 0.830 | A | 0.096 | 0.145 | 0.839 |
| B | 0.112 | 0.000 | 0.005 | B | 0.136 | 0.018 | 0.148 |
| C | 0.556 | 0.208 | 0.165 | C | 0.769 | 0.837 | 0.013 |

| Item 3 | | | | Item 8 | | | |
|----------|-------|-------|-------|----------|-------|-------|-------|
| | State | | | | State | | |
| Response | 1 | 2 | 3 | Response | 1 | 2 | 3 |
| A | 0.511 | 0.729 | 0.819 | A | 0.086 | 0.201 | 0.833 |
| B | 0.048 | 0.025 | 0.072 | B | 0.125 | 0.030 | 0.137 |
| C | 0.441 | 0.246 | 0.110 | C | 0.789 | 0.769 | 0.029 |

| Item 4 | | | | Item 9 | | | |
|----------|-------|-------|-------|----------|-------|-------|-------|
| | State | | | | State | | |
| Response | 1 | 2 | 3 | Response | 1 | 2 | 3 |
| A | 0.744 | 0.958 | 0.946 | A | 0.622 | 0.953 | 0.923 |
| B | 0.070 | 0.000 | 0.009 | B | 0.072 | 0.012 | 0.026 |
| C | 0.185 | 0.042 | 0.045 | C | 0.306 | 0.035 | 0.051 |

| Item 5 | | | | Item 10 | | | |
|----------|-------|-------|-------|----------|-------|-------|-------|
| | State | | | | State | | |
| Response | 1 | 2 | 3 | Response | 1 | 2 | 3 |
| A | 0.729 | 0.945 | 0.937 | A | 0.276 | 0.899 | 0.841 |
| B | 0.202 | 0.036 | 0.063 | B | 0.230 | 0.016 | 0.120 |
| C | 0.069 | 0.019 | 0.000 | C | 0.493 | 0.085 | 0.038 |

A: anti-corruption measure accomplished; B: anti-corruption measure not accomplished because it was not expected by the PTPC; C: anti-corruption measure not accomplished even if it was expected by the PTPC.

Table 2 Estimates of the initial probabilities (a) and of the transition probabilities from 2014 to 2015 (b) and from 2015 to 2016 (c)

| (a) | | (b) | | | | (c) | | | |
|-------|---------------------|-------|-------|-------|-------|-------|-------|-------|-------|
| State | Initial probability | State | 1 | 2 | 3 | State | 1 | 2 | 3 |
| 1 | 0.412 | 1 | 0.445 | 0.339 | 0.216 | 1 | 0.798 | 0.000 | 0.202 |
| 2 | 0.450 | 2 | 0.013 | 0.553 | 0.434 | 2 | 0.000 | 0.717 | 0.283 |
| 3 | 0.139 | 3 | 0.045 | 0.228 | 0.727 | 3 | 0.014 | 0.085 | 0.901 |

5 Conclusions

In this work, a longitudinal analysis of the Italian municipalities compliance as regards anti-corruption measures is presented. The information contained in the annual reports of the supervisor for corruption prevention (RPC forms) are exploited with reference to a set of items about the accomplishment of anti-corruption measures. Data about a sample of more than 200 municipalities are used for the years 2014, 2015 and 2016. A latent Markov model is fitted on the data at issue, finding evidence of three states of increasing virtuosity in terms of anti-corruption behaviour. Results show that in 2014 – year of introduction of the new Italian anti-corruption law – less than 15% of the sample belongs to the group of the most virtuous municipalities, then only few administrations have accomplished measures for contrasting corruptive events. The analysis of the transition matrices reveals high probabilities to move to higher virtuosity states, even though a clear tendency to stay in the current state is observable, especially in the last year.

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