Approximation of measurement of the dedication in research of the universities in Colombia from the knowledge by institution

Presented by: Iván Camhilo Romero Sanabria.
Directors: Wilmer Darío Pineda Ríos & Dagoberto Bermudez Rubio

Faculty of Statistics, Santo Tomás University, Bogotá

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Resumen

El objeto de estudio del proyecto que se realizó es el de implementar un listado de modelos, en los cuales se busca observar un paralelo entre los modelos, los cuales, logren determinar cuál es el que se comporta de la mejor manera, logrando así explicar la producción científica, a través de la información que se tiene sobre el tipo de investigador. El objetivo es analizar las capacidades de la investigación en universidades colombianas, a partir de los análisis de los productos de conocimiento científico y tecnológico.

Los modelos que se buscan contrastar para dar respuesta a la producción científica y tecnológica son:

- Modelos de regresión para datos de conteo
- Modelos de regresión Hurdle

Dentro de los cuales se derivan varias regresiones por modelo.

Palabras Claves: Capacidades en investigación, universidades, indicadores de recursos humanos en Ciencia y Tecnología (CyT), Regresión Gamma, Inferencia, Regresión Poisson, Poisson truncada, Modelo truncados e inflados por ceros.

Abstract

The object of study of the project that was conducted is to implement a list of models in which it seeks to observe a parallel between models which achieve determine which behaves the best way to achieving explain scientific production, to through the information we have about the type of research. The objective is to analyze the capabilities of research in Colombian universities from the analysis of the products of scientific and technological knowledge.

The models seek contrast to respond to the scientific and technological production are:

- Regression models for count data
- Regression models Hurdle

Within which they derive several regressions model.

Keywords: Capacity research institutes, universities, indicators of human resources in Science and Technology (S & T), Gamma regression, Inference, Poisson regression, Poisson truncated, truncated and inflated zeros Model.

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Introduction

The construction of human resource trajectory indicators in Colombia represents the capacity of the National System of Science and Technology; In terms of researchers linked to universities that are generally involved, both in the production of new knowledge and in the training of human resources with research competencies, although this does not happen in all cases, this role of universities gives them A significant strategic position in the National System of Science and Technology. The analysis population comprises the group of researchers active in research groups supported by at least one university, because they show production associated with their activity in Science, Technology and Innovation, following the criteria defined in the recognition and measurement models of research groups proposed by Colciencias (2008, 2013)

General objective

The object of the study is to analyze and contrast the research capacities of Colombian universities, from a perspective of the capacity of analysis of the products of scientific and technological knowledge, generated by the type of researcher linked to these institutions. Specific objective

1. Review of the state of the art of the measurement of research capacities, applied to Colombian universities

2. Identify the models used by Colombian universities in the representation of knowledge-based capacity

3. Implementation and contrast of models for the measurement of research capacity from production reported in Colombian universities

Approach to State of Art

Traditionally, the indicators used for the measurement of science and technology start from an input-output perspective (Entre la legitimidad, la normatividad y la práctica, Capitulo 7), With human resources and expenditures as inputs, while bibliographic production and intellectual property constitute the products. However, the emergence of new actors and institutions in the relationships between science, technology and innovation, with their own interests and needs, generates new demands on the indicators, metrics and sources of information used, with the purpose of making better representations that account, on one side of the institutional configuration and the activities and interests of the actors involved in Science and Technology activities (Lepori, et al., 2008).

It is proposed to measure the skills based on knowledge applicable to universities in Colombia, which is based on the exploration and analysis of the information that is reported in Scienti. This allows us to move towards the construction of an approach for the measurement of knowledge-based capacities in universities, by reviewing the theoretical aspects associated with the National Innovation Systems and the specific documentation for the Colombian case.

It is therefore particularly interesting to note the developments that have taken place around the notion of forms of capital associated with the processes of generation and use of knowledge, specifically from the approaches of the knowledge-based economy and theories of resources and capabilities, Which place other forms of capital and employ an alternative notion of capital associated with knowledge-based intangibles and the inseparability of such knowledge from the individuals who generate and use it (Margaret M. Blair, 2011) All within the framework of building competitive advantage of organizations and their position in a changing environment, in this case an environment called National System of Science and Technology and Innovation (SNCTI) Of which universities are relevant actors.

In this sense, human capital, linked to the SNCTI refers to the intangible assets that include the know-how, skills, abilities and skills of the people that allow by the dedication to specific activities, the development of knowledge generation processes and the obtaining of scientific products , Technological objects and, in general, objects of knowledge (Margaret M. Blair, 2011; H. Jaramillo & Forero, 2001a; G. Roos, A. Bainbridge, & K. Jacobsen, 2002a; J. Roos & Whitehill, 1998a; K. E. Sveiby, 1997).

Justification

It is considered a review of the conceptual and methodological elements for the measurement of capacities based on scientific and technological knowledge in Colombian universities, based on the review carried out, the notion of human capital is proposed as a central category in the analysis.
From the perspective proposed by Nahapiet (2011), The approach of work should focus on the relational dimension of social capital, understood as the quality of the links that exist between individuals in the specific context of the university, in this case based on human resources and forms of organization, which Use proxies to research groups. These relationships make it possible to understand the dynamics of the capacities in the organizations that are part of the fabric of the system of science, technology and innovation of the developing countries from the human capital trajectories.

The study of the research has the objective of presenting different models with which the scientific and technological production in the Colombian universities is contrasted, through information about the researchers associated with these institutions. We are looking for to use different models to the linear one because the universities use linear models, not knowing that these models are affected since many investigators do not report their scientific production either because they are no longer interested to report it in CvLAC or simply because they have positions so important that It does not matter whether these scientific productions are reported.

The problem is that many people not reporting these scientific outputs are left with zeroes and when applying the linear model this is affected by the number of zeros in the databases. With this, the application of models that are not affected by these zeros is sought.

The models that are tried to contrast to give answer to the scientific and technological production are:

- Regression models for counting data
- Hurdle Regression Models

Within the regression model for counting data, it is distinguished by the application of different regressions, within which they stand out.

- Poisson Regression
- Negative binomial Regression
- Zero-inflated Poisson Regression

The information used for the construction of these models is very sensitive to changes in the measurement applied by Colciencias in the calls for recognition and measurement of research groups and researchers. The call becomes the main motivation that researchers should keep their information updated, in addition to the timely gestation of the curricula by the leaders of the groups. The models that are sought to present obey a cut of information of the applications CvLAC and GrupLAC of the platform ScienTI after the call 693 of 2014

The purpose of the study is that, through explanatory variables of the researchers, it is possible to arrive at an adequate approximation of the scientific production, using the proposed models and determining which is the model that gives better results.

To improve the results of the presented models, a Bayesian analysis will be used, the a priori distributions named later, and the posteriori will be obtained by means of Monte-Carlo integration with important sampling. With what in the end it is tried to contrast the simulations against the real data, since the real information is available.

Theoretical framework

This session deals with two special cases that may appear when working with counts. Although both cases are fundamentally different, they have the same element in common: 0. It begins by talking about models that do not allow the response variable to be 0 (Zero truncated models), and that therefore they never predict a value of 0 for her. Subsequently we will move to Zero inflated models, in which, for some reason, there are more observations with a value 0 than would be expected per a Poisson or negative binomial distribution.

For data that take integer and non-negative values, the Poisson distribution and the negative Binomial are used. In the Poisson regression, it is assumed that the VR is distributed per a Poisson function with a parameter "mu" μ (which is both the mean and the variance). The problem is that the Poisson distribution does not exclude zeros, that is, it predicts values of 0 for the RV, especially when the values of μ are low.

The common regression model for counting data is Poisson regression. This model has been widely described in the statistical literature in general and in specific texts for counting data, so that only its main characteristics and its specification within a regression structure and in terms of its likelihood function. Like any regression model, the Poisson regression requires a correct specification of the conditional mean, if, that the conditional distribution for the response variable is correctly specified as well as the parameter related to its expected value. For the Poisson regression, it is assumed that the conditional distribution of y given x is distributed as a Poisson random variable.

$$f(y|x) = \frac{e^{-\mu(x)}\mu(x)^y}{y!}$$

Where

$$E(Y|X_1 \dots X_k) = \mu(x) = \mu(X_1 \dots X_k) = \exp(\beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k)$$

One of the main reasons why the Poisson model fails is unobserved heterogeneity. This means that there are unobserved factors, especially characteristics of individuals, that exert some influence on the variability related to the response variable.
The problem is that unobserved heterogeneity may have some consequences for statistical inference processes. In the first place, it can introduce over dispersion and, secondly, an excessive number of zeros. This heterogeneity, ignored by the Poisson model, can be explicitly modeled using negative binomial regression.

The density function for the negative binomial distribution is determined by the following expression:

$$f(y|x) = \frac{\Gamma(y+\alpha^{-1})}{\Gamma(y+1)\Gamma(\alpha^{-1})} \left(\frac{\alpha^{-1}}{\alpha^{-1}+\mu}\right)^{\alpha^{-1}} \left(\frac{\mu}{\alpha^{-1}+\mu}\right)^{y}$$

Where α is a scatter parameter and Γ is Gamma function.

The log-likelihood function for the negative binomial regression model, with quadratic variance function, after some algebraic manipulation of the density function is:

$$L(\beta,\alpha) = \sum_{i=1}^{n} \left\{ \sum_{j=0}^{y_i-1} \log(j+\alpha^{1}) - \log(Y_i!) - (Y_i+\alpha^{1})\log(1+\alpha^{*}\exp(X_i\beta)) + Y_i\log(\alpha+Y_iX_i\beta) \right\}$$

There are at least two ways in which the negative binomial distribution can be derived; The most common is to assume that we are faced with the presence of a mixture of distributions in which the observed data are distributed as a Poisson, but an element of unobserved individual heterogeneity is assumed (following a gamma distribution in its formulation Classical) that reflects the fact that the true mean has not been measured perfectly.

The second assumes that there is a form of dependence between events, in the sense that the occurrence of one event increases the probability of occurrence of later events, although the latter can only be elucidated in longitudinal studies.

While it is true that the negative binomial model has been developed to explicitly model unobserved heterogeneity, it is also true that the same heterogeneity is caused by an excessive number of zeros. That is, observe more zeros than those that are consistent with the Poisson model. It is possible that the random mechanism that gave rise to the counting data shows a higher concentration for some specific value, which may be zero or any other positive value. This implies that such a value has a greater probability of occurrence than that specified by the Poisson distribution or any other distribution.

For the specific case of the zeros and in the context of the use of the health services it is possible that the zeros have a double origin. This means that you have a mix of distributions, so it would not be appropriate to assume in this instance that zeros and nonzero have been generated by the same process. In any case, if one has information regarding the origin of the zeros, one can estimate the parameters related to a distribution with values concentrated in zero. The models for zero-inflated counting data give more weight to the probability that the counting variable is equal to zero, by incorporating a mechanism that divides subjects with a value of zero, and whose probability is $p(x_{1i}, \beta_1)$, and individuals with positive and probability values 1- $p(x_{1i}, \beta_1)$.

Consequently, the probability function for a zero-inflated Poisson regression model is a mixture of a standard Poisson model and a distribution with Concentrated mass function at zero. The zero-inflated Poisson regression model can be specified as follows. First, the following quantities are defined

$$\phi_1 = \Pr(y_i = 0)$$

and

$$\mu_i = \mu(x_i, \beta)$$

The first quantity is the probability that the counting variable is zero and the second is the expected value when the counting variable assumes a positive value.

In the first instance, a statistical way must be found to express ϕ_i, so that only non-negative values are obtained. For this reason, Lambert proposed a parameterization for ϕ_i based on the logistic function and located it in a regression structure, such that a vector of covariables Z_i could be used for model ϕ_i, that is:

$$y_i = 0$$

$$y_i \sim \Pr(\mu_i)$$

$$\varphi_i = \frac{\exp(z_i y)}{1 + \exp(z_i y)}$$

In such a case, and in terms of a regression model, the focus is on calculating (γ, β). If we further define an indicator variable to denote that y takes the value of 1 if $y_i = 0$, and zero in any other case, then the joint log-likelihood function, after omitting the constants, is:

$$L(\beta, y) = \sum_{i=1}^{n} 1(y_i = 0)\log(\exp(z_i y) + \exp(-\exp(x_i\beta) + \sum_{i=1}^{n}(1 - 1(y_i = 0)(y_i x_i \beta$$
$$- \exp(x_i b) - \sum_{i=1}^{n} \log(1 + \exp(z_i y)$$

This function can be used to find the estimators of β (of prime interest) as well as γ. It is worth noting that although the derivation of the log-likelihood function in terms of the zero-inflated Poisson regression model has been made here, it is also possible to do so for the zero-inflated negative binomial regression model.

Hurdle Regression Models

Like the regression model for zero-inflated counting data, the Hurdle model assumes the presence of a mix of distributions, except that the model has a two-part interpretation. The first refers to a model with a binary response variable and the second to a truncated count data model at zero. Consequently, this two-part configuration allows the interpretation that positive values are generated whenever the threshold (Hurdle) at zero has been crossed. Therefore, the first part models the probability that the threshold is crossed, while the second part models the expected value of the positive values.

In a slightly more formal way, the Hurdle model can be specified as follows. Since a mixture of two distributions is assumed, the moments of such distributions differ from a Poisson distribution and can be specified as follows:

$$P(y = 0) = f_1(0)$$

$$P(y = j) = \frac{1 - f_1(0)}{1 - f_2(0)} f_2(y)$$

Where $j > 0$

Which collapses to the Poisson model only if f1 (·) = f2 (·). In other words, it is not assumed that the processes that generated the zeros and positive values are equal. In simpler terms, the Hurdle model is a finite mixture generated by combining a density function that gives rise to zeros, and another density function that produces positive values. Hence the moments of the Hurdle model are determined by the probability of crossing the threshold and by the moments of the truncated-in-zero density function, that is:

$$E(y|x) = P[y > 0|x]E_{y>0}[y|y > 0, x]$$

Therefore, the global model, with zeros and positive values, is used to estimate the parame ters linked to both densities. To estimate the parameters of the Hurdle model, some probability distribution can be used for counting variables (Poisson or negative binomial), only without losing sight of a truncated-in-zero variable.

General information

This section presents general information for five universities in Bogotá. Within this section we observe the relevant information for each university, the selection of universities, was based on similar behaviors that have universities in general. The selected universities are:

1. University Santo Tomas
2. University of Rosario
3. Antonio Nariño University
4. Jorge Tadeo Lozano University
5. Gran Colombia University

University Santo Tomas	Woman	Man	Total
Doctorate	36	107	143
Specialization	178	324	502
Máster	267	462	729
Other	14	22	36
Pregrado	154	299	453
Total	649	1214	1863

In the Santo Tomás University, it is evident that many the researchers that have in the University, they have a title of mastery, soon they are the investigators with a specialization. A similar case occurs with male researchers; it is generally said that there are twice as many men as women within the research within Santo Tomas University.

Jorge Tadeo Lozano University	Woman	Man	Total
Doctorate	21	45	66
Specialization	55	127	182
Máster	144	290	434
Other	7	8	15
Pregrado	83	132	215
Total	310	602	912

Jorge Tadeo Lozano University presents a behavior like that of Santo Tomás, since most of the researchers, with master's degrees, but it should be noted that there are more researchers with an undergraduate degree than with specializations.

Gran Colombia University	Woman	Man	Total
Doctorate	4	10	14
Specialization	85	175	260
Máster	86	168	254
Other	5	6	11

Pregrado	57	134	191
Total	237	493	730

Within the Gran Colombia University, it can be observed that there is a similar percentage of researchers, both with masters and with specialization. As in previous universities, men double women. It is the university with less number of PhD, compared with the other universities observed.

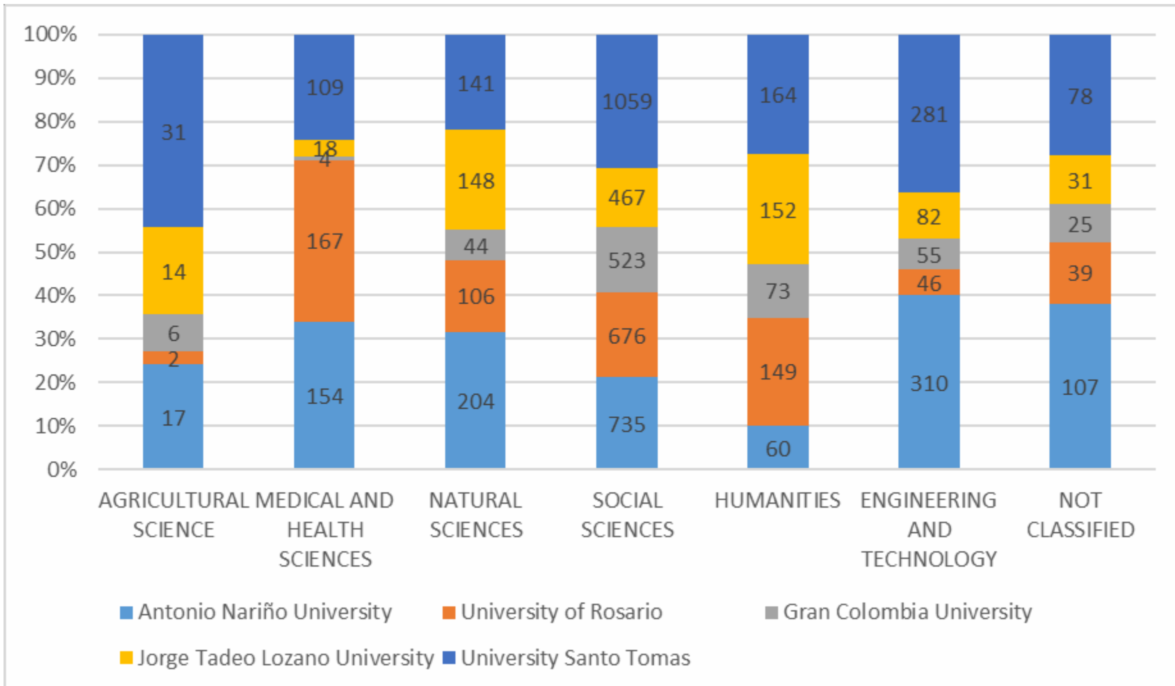
University of Rosario	Woman	Man	Total
Doctorate	50	95	145
Specialization	76	109	185
Máster	164	256	420
Other	14	18	32
Pregrado	172	231	403
Total	476	709	1185

Rosary University is the one that counts on greater number of PhD, in comparison with the other universities, counts on a great number of investigators with mastery and with title of undergraduate.

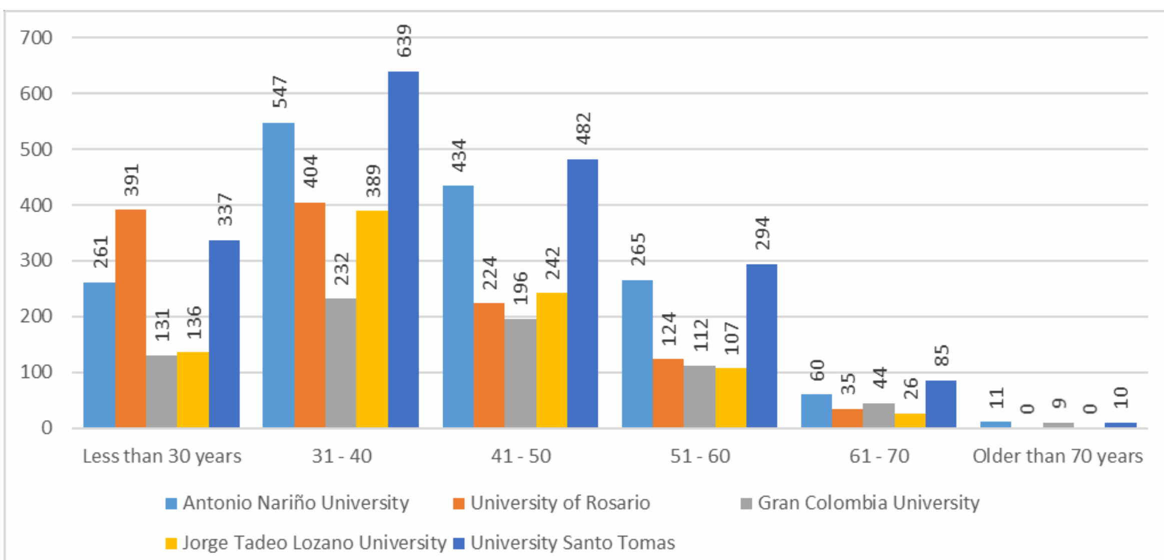
Antonio Nariño University	Woman	Man	Total
Doctorate	22	50	72
Specialization	244	420	664
Máster	159	295	454
Other	10	12	22
Pregrado	128	247	375
Total	563	1024	1587

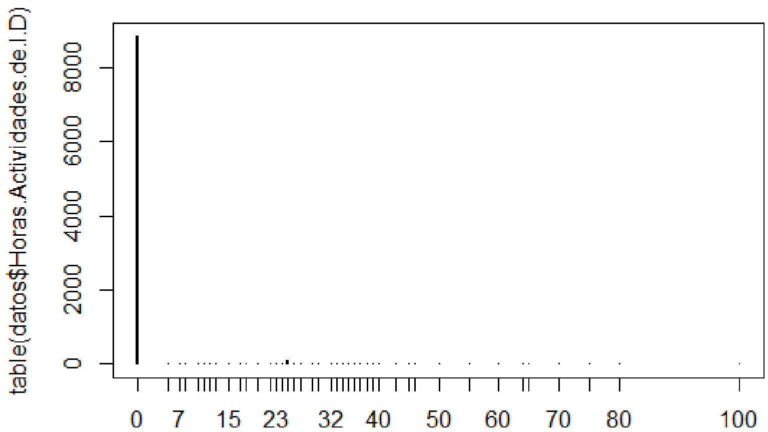
Antonio Nariño University has a large percentage of researchers with specialization, participation that exceeds master's degree, is the second university with the largest number of researchers.

The following graph shows the number of researchers per area of knowledge, for each of the universities, it is highlighted that the University Antonio Nariño is one of the most important, with also the University of Santo Tomás, the university with the lowest participation Is the Gran Colombia University. Antonio Nariño University stands out mainly in social sciences, although its greater participation percentage is in agricultural sciences. All the observed universities stand out in social sciences, but they do not have great percentages of participation in agricultural sciences. The preferred areas after the social sciences are the natural sciences and the humanities.



This graph presents the number of researchers by age group, it is observed that in most universities, the largest number of researchers is concentrated in ages between 30 and 50 years. However, the University of the Rosary relies heavily on the capacity of its young researchers, and it is the university that has the largest number of researchers under the age of 30. It is also evident that the universities, Antonio Nariño, Gran Colombia and Santo Tomás, believe in the contributions of highly experienced researchers, and that is why they are the only ones that have researchers over 70 years. The universities with the largest number of researchers are Universidad Santo Tomas and Universidad Antonio Nariño.

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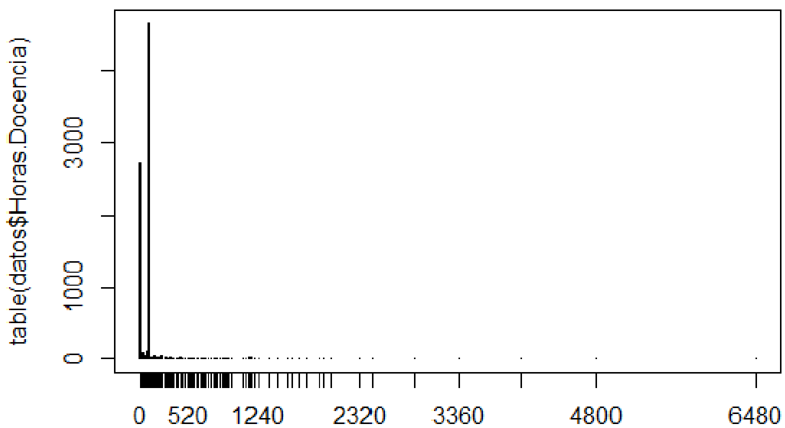
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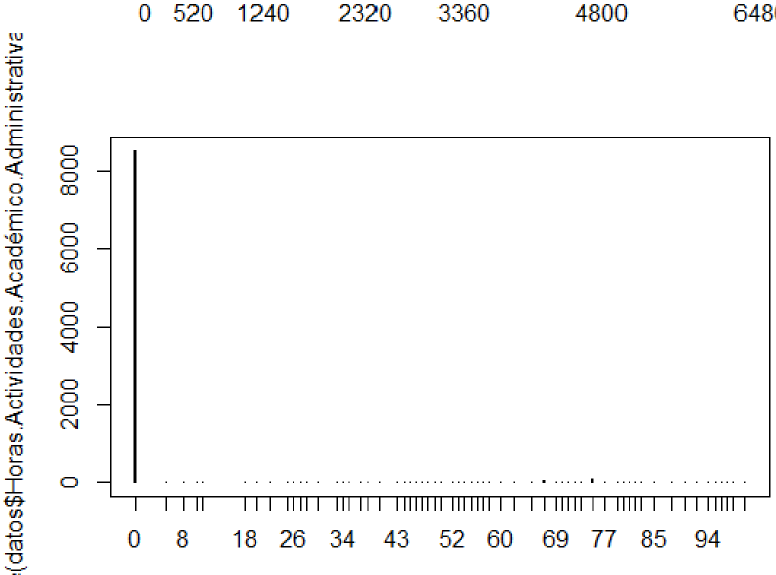
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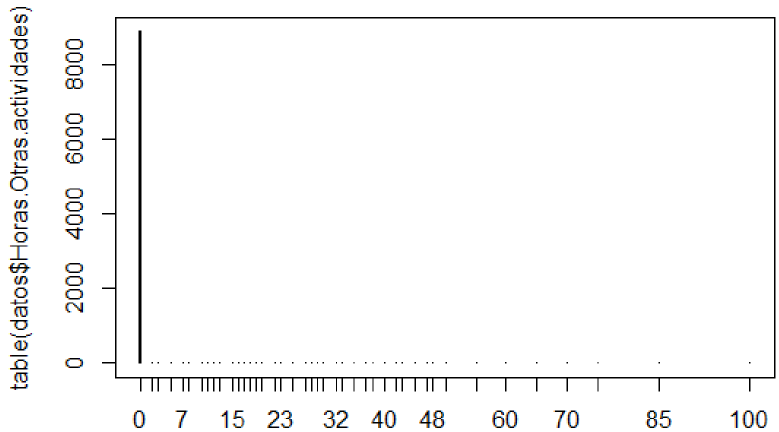

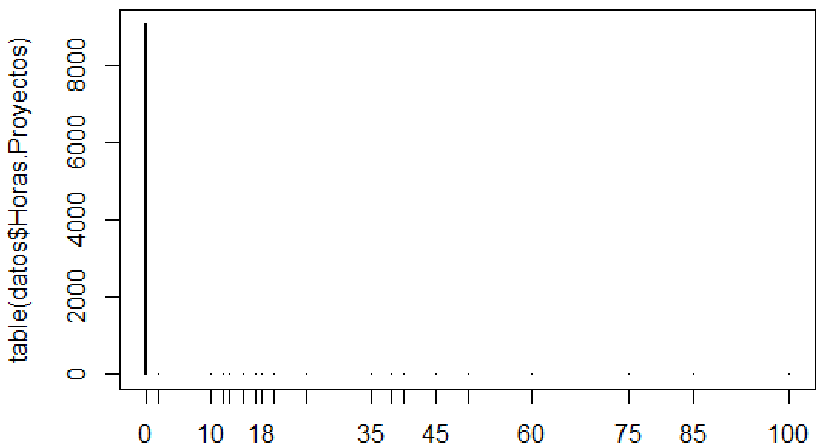

In the previous graphs, you can observe as the information of dedication in hours in activities of I & D, teaching, administrative activities, projects and other activities. It is strongly influenced by values of zeros, since the largest participations are in zero or values close to zero, as evidenced by dedication in teacher hours.

```
> summary(posterior)

Iterations = 5001:15000
Thinning interval = 1
Number of chains = 1
Sample size per chain = 10000

1. Empirical mean and standard deviation for each variable,
   plus standard error of the mean:

                                                 Mean        SD  Naive SE Time-series SE
(Intercept)                                -1.018e+03 6.626e+02 6.626e+00      1.573e+02
Horas.Docencia                             -1.506e-03 1.246e-04 1.246e-06      6.189e-06
Horas.Actividades.Académico.Administrativas -2.702e-03 7.278e-04 7.278e-06      3.634e-05
InstitucionUniversidad del Rosario          1.019e+03 6.626e+02 6.626e+00      1.573e+02
InstitucionUniversidad GranColombia         1.019e+03 6.626e+02 6.626e+00      1.573e+02
InstitucionUniversidad Jorge Tadeo Lozano  -2.798e+03 1.897e+03 1.897e+01      8.150e+02
InstitucionUniversidad Santo Tomás          1.018e+03 6.626e+02 6.626e+00      1.573e+02
Horas.Otras.actividades                     2.604e-02 6.871e-04 6.871e-06      3.382e-05
Horas.Proyectos                            -6.557e-03 2.456e-03 2.456e-05      1.247e-04

2. Quantiles for each variable:

                                                 2.5%        25%        50%        75%      97.5%
(Intercept)                                -2.439e+03 -1.497e+03 -9.228e+02 -4.671e+02 -5.881e+01
Horas.Docencia                             -1.762e-03 -1.585e-03 -1.507e-03 -1.421e-03 -1.263e-03
Horas.Actividades.Académico.Administrativas -4.185e-03 -3.177e-03 -2.664e-03 -2.210e-03 -1.237e-03
InstitucionUniversidad del Rosario          6.035e+01  4.686e+02  9.244e+02  1.499e+03  2.441e+03
InstitucionUniversidad GranColombia         5.992e+01  4.682e+02  9.239e+02  1.498e+03  2.440e+03
InstitucionUniversidad Jorge Tadeo Lozano  -5.286e+03 -4.247e+03 -3.396e+03 -1.564e+03  1.243e+03
InstitucionUniversidad Santo Tomás          5.915e+01  4.674e+02  9.232e+02  1.497e+03  2.440e+03
Horas.Otras.actividades                     2.470e-02  2.558e-02  2.604e-02  2.651e-02  2.740e-02
Horas.Proyectos                            -1.140e-02 -8.204e-03 -6.394e-03 -4.872e-03 -1.956e-03
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Estimates with 10,000 simulations show that the variables that contribute to research and development are the universities that one of their missions or approaches is research. It is also interesting to observe how getting involved in other activities reduces dedication in research, and this is something that was evident, since usually people who perform other activities such as teaching or administrative work, have little time for research and development.

```
> summary(posterior)

Iterations = 5001:1005000
Thinning interval = 1
Number of chains = 1
Sample size per chain = 1e+06

1. Empirical mean and standard deviation for each variable,
   plus standard error of the mean:

                                                 Mean        SD  Naive SE Time-series SE
(Intercept)                                -1.528e+04 1.164e+04 1.164e+01      4.568e+03
Horas.Docencia                             -1.507e-03 1.267e-04 1.267e-07      6.221e-07
Horas.Actividades.Académico.Administrativas -2.638e-03 7.027e-04 7.027e-07      3.439e-06
InstitucionUniversidad del Rosario          1.529e+04 1.164e+04 1.164e+01      4.568e+03
InstitucionUniversidad GranColombia         1.529e+04 1.164e+04 1.164e+01      4.568e+03
InstitucionUniversidad Jorge Tadeo Lozano  -2.615e+04 1.500e+04 1.500e+01      5.633e+03
InstitucionUniversidad Santo Tomás          1.528e+04 1.164e+04 1.164e+01      4.568e+03
Horas.Otras.actividades                     2.602e-02 6.688e-04 6.688e-07      3.272e-06
Horas.Proyectos                            -6.608e-03 2.398e-03 2.398e-06      1.178e-05

2. Quantiles for each variable:

                                                 2.5%        25%        50%        75%      97.5%
(Intercept)                                -3.736e+04 -2.555e+04 -1.189e+04 -4.881e+03 -3.904e+02
Horas.Docencia                             -1.763e-03 -1.592e-03 -1.505e-03 -1.421e-03 -1.265e-03
Horas.Actividades.Académico.Administrativas -4.027e-03 -3.114e-03 -2.635e-03 -2.161e-03 -1.277e-03
InstitucionUniversidad del Rosario          3.919e+02  4.882e+03  1.189e+04  2.555e+04  3.736e+04
InstitucionUniversidad GranColombia         3.915e+02  4.882e+03  1.189e+04  2.555e+04  3.736e+04
InstitucionUniversidad Jorge Tadeo Lozano  -4.920e+04 -3.789e+04 -2.899e+04 -1.645e+04  6.033e+03
InstitucionUniversidad Santo Tomás          3.907e+02  4.881e+03  1.189e+04  2.555e+04  3.736e+04
Horas.Otras.actividades                     2.470e-02  2.557e-02  2.603e-02  2.647e-02  2.731e-02
Horas.Proyectos                            -1.148e-02 -8.192e-03 -6.556e-03 -4.954e-03 -2.078e-03
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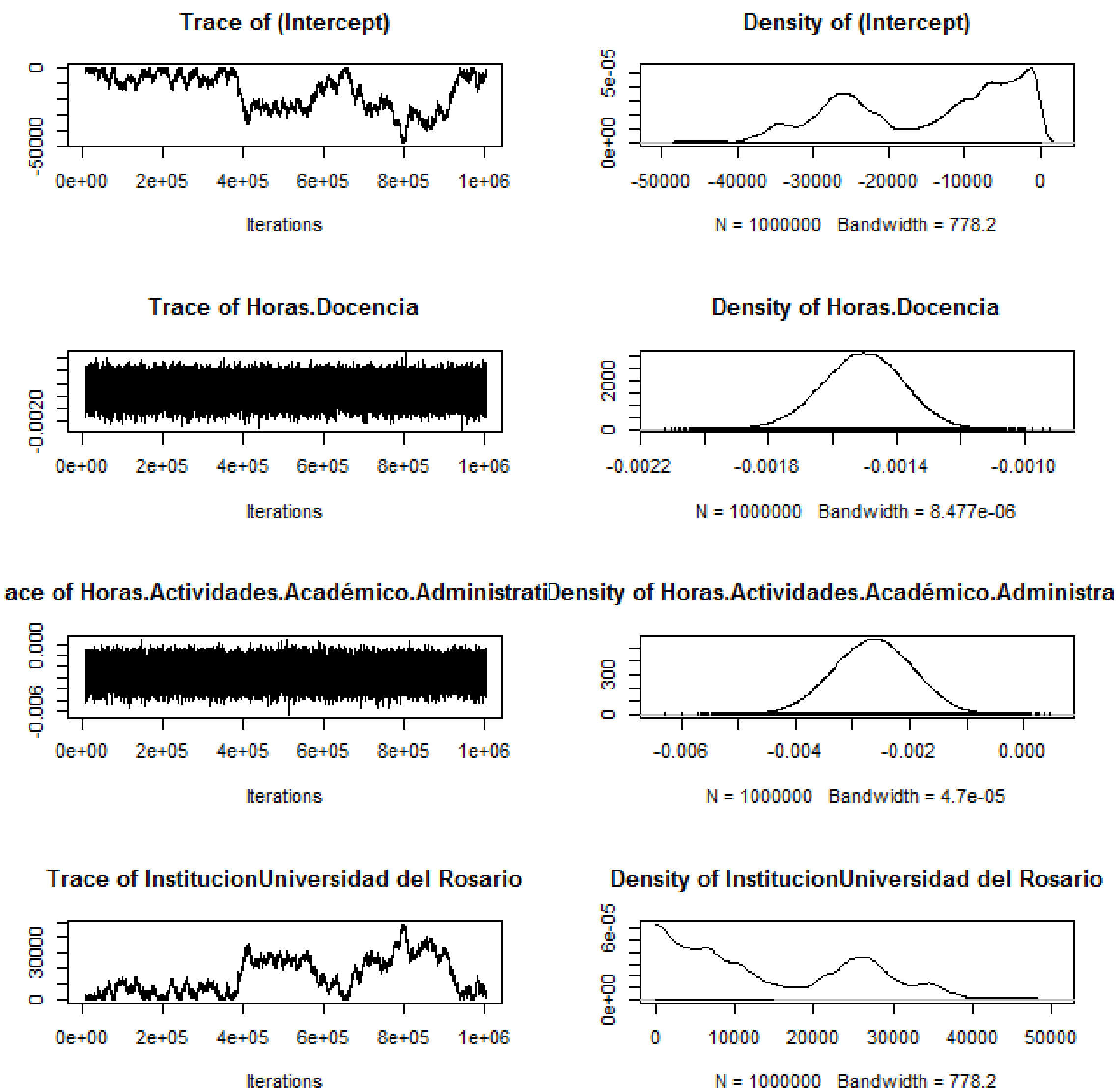
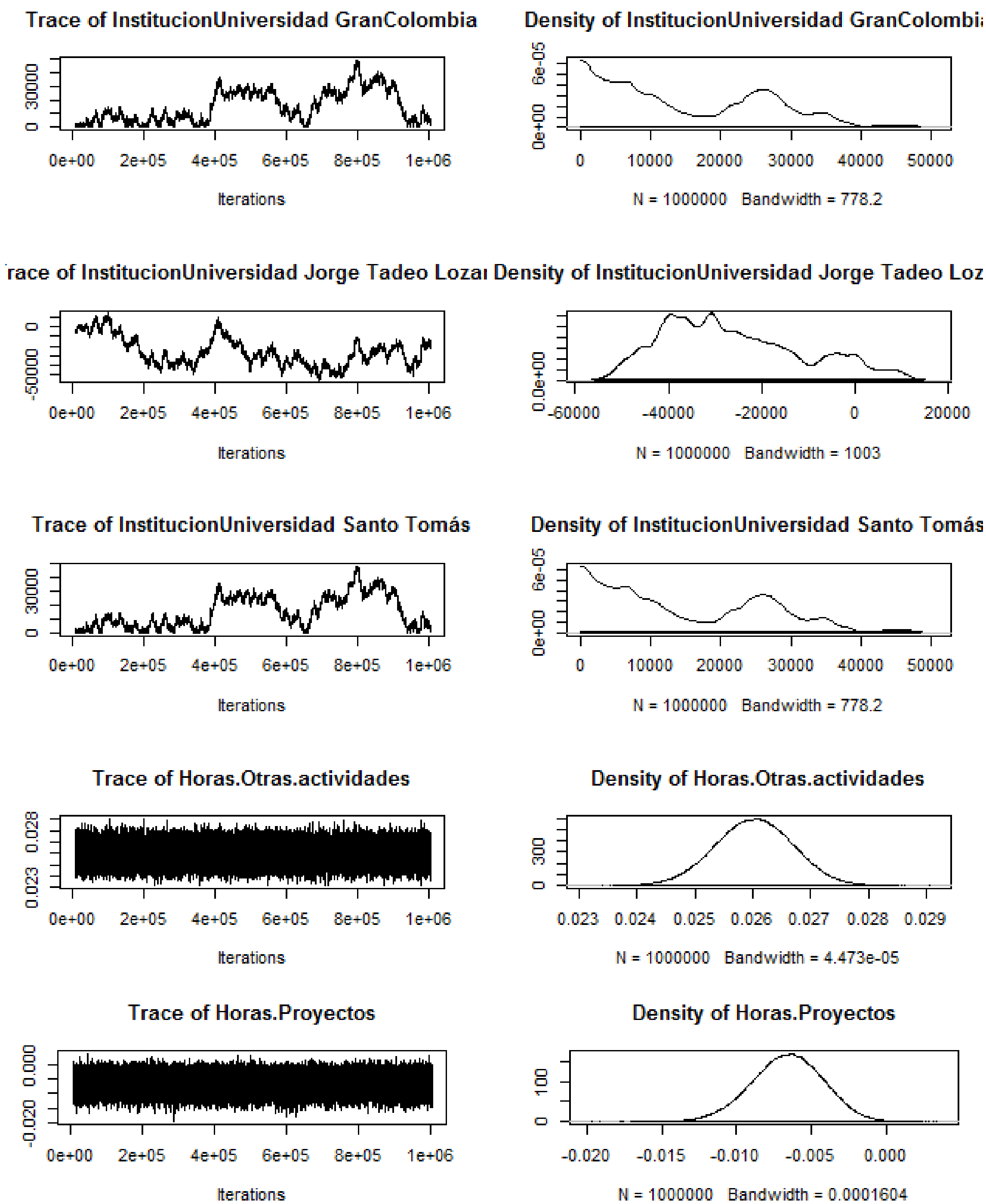
Estimates with 1,000,000 simulations, it is evident what already mentioned



In these graphs, we observe how the behavior of the dedication in research and development, depending on each of the variables that influence the model. In the graphs of the left the markov chains are observed, which show that along the iterations the variables tend to stabilize, but this does not happen in the case of the universities, since, as can be observed, the behavior of the research within these is very changeable. There are specific cases where in certain universities the behaviors have peaks or tendencies, but these do not manage to remain over time.

If we observe the graphs on the right, these evidences, the densities of each one of the observed variables, as can be predicted the graph of the variables of the iterations, the ones with the best behavior present, are the ones that have the best density graphs. This is contrary to what happens with the variables of the universities, which show that their densities show some trends, either to rise or fall.


Trace of InstitucionUniversidad GranColombia
Iterations
Density of InstitucionUniversidad GranColombi
N = 1000000 Bandwidth = 778.2
race of InstitucionUniversidad Jorge Tadeo Loza
Iterations
Density of InstitucionUniversidad Jorge Tadeo Loz
N = 1000000 Bandwidth = 1003
Trace of InstitucionUniversidad Santo Tomás
Iterations
Density of InstitucionUniversidad Santo Tomás
N = 1000000 Bandwidth = 778.2
Trace of Horas.Otras.actividades
Iterations
Density of Horas.Otras.actividades
N = 1000000 Bandwidth = 4.473e-05
Trace of Horas.Proyectos
Iterations
Density of Horas.Proyectos
N = 1000000 Bandwidth = 0.0001604

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