Analysis of local fiscal deficits in Mexico using Artificial Neural Networks

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Abstract
This paper contains an analysis of local governments fiscal deficits in Mexico using Machine Learning Methods. We use Artificial Neural Networks (ANN) to predict local public deficits using the expenditure side chapters of Municipal budgets as feature variables. Our scientific objective is to detect which part of the budget is more influential or can be assumed to induce the local Municipal deficits in general. We obtained the weights from the network and used them to construct a contribution measure in order to evaluate the importance of each fiscal expenditure. The main finding is that Local Public Investment, despite being the second largest expenditure, has a very small effect on prediction compared with current expenditure. This result has a very important meaning: That no fiscal deficit of Municipal Governments can be justified in terms of better or higher public investment in the form of social capital and infrastructure. In other words, local fiscal deficits are driven almost entirely by Municipal current and operational expenses.
Key words: Local Public Deficit, Artificial Neural Networks, Local Public Expenditure
JEL classification: C45, H72, H68.

Análisis de los déficits fiscales locales en México a través de Redes Neurales Artificiales

Resumen
Este documento contiene un análisis sobre los déficits fiscales de los gobiernos locales en México mediante métodos de Aprendizaje Maquina. Utilizamos la técnica de Redes Neurales Artificial (ANN) para predecir los déficits públicos locales utilizando los capítulos de gastos de los presupuestos municipales como variables independientes. Nuestro objetivo científico es detectar la parte del presupuesto de egresos que más influye o que induce los déficits municipales locales en general. Obtuvimos las ponderaciones de red neuronal y los usamos para construir una medida de contribución con el fin de evaluar la importancia de cada gasto Municipal. El principal hallazgo es que la inversión pública local, a pesar de ser el segundo rubro más grande, tiene un efecto reducido en la predicción en comparación con el gasto corriente. Este resultado tiene un significado muy importante: Que ningún déficit fiscal de los gobiernos municipales puede justificarse en términos de una mejor o mayor inversión pública en forma de capital social e infraestructura. En otras palabras, el déficit fiscal local se deriva principalmente de los gastos corrientes y operativos.
Palabras clave: Déficit Públicos Locales, Redes Neuronales Artificiales, Gasto Público Local
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Introduction

When analyzing economic phenomena, we usually try to use Parametric methods in search of parameters that have economic interpretation and meaning. The drawback is that Parametric methods rely on assumptions that sometimes are hard to support, depending on the problem at hand. For example, we commonly assume that some variables have a distribution among the Parametric family (e.g. Normal). If the assumptions cannot be supported, then we could transform or adjust the data to meet our assumptions though this might not be always successful. We also have at our disposal a wide range of statistical tests and methods to improve in statistical analysis and forecasting. Although we cannot deny the usefulness of such methods when they are properly handled, sometimes we may also improve our understanding using a more flexible approach.

A very broad field of nonparametric methods are also being developed and used to produce important economic analysis for example, the methods of Artificial Neural Networks (ANN) which is part of a subject called Machine Learning. The central paradigm in this method is to let the data determine the model rather than force the data to fit a pre-set model, as with parametric methods. The name of nonparametric clearly express the premise that, rather than imposing any distribution to the data, we let the data to speak for itself. In the specific case of ANN, we let the data determine the model that is better suited for prediction through supervised learning.

Perhaps one critique of machine learning methods is the lack of a straightforward interpretation of the estimates (weights) obtained. The estimates of an ANN have no economic meaning by themselves but on the other hand, their implications can be easily understood. Nonparametric methods are distribution free and therefore they need less strict assumption about the nature of the population, and they can be applied to all sorts of data.

This work contains a simple formulation of Artificial Neural Networks and their practical application to a public finance problem. There is little precedent in the use of machine learning methods in public finance, specifically the forecasting of local deficits. As far as the author's knowledge, there is no applied research of ANN on local public finance data. Hence there is a strong motivation to use machine learning methods to research on important questions in the area of local public economics.

Most parametric analysis using public finance data have severe problems of endogeneity and heteroskedasticity at least. Nonparametric methods can go around those problems by requiring fewer assumptions in the nature of the data. In this respect Machine Learning methods such as ANN can overcome such problems by making better classification and obtaining strong results for simple scientific questions. In saying this, we must clarify that our scientific objective is not the forecasting of local fiscal deficits *per se*, but to evaluate which features of the municipal budget (explanatory variables) are influencing such deficits. We are looking for the weights that define the statistical model without imposing any previous assumptions on the data.

Our quest is simple: The size and the relation among weights within the ANN will tell us how important each feature in our model is. Because we are only interested in the practical applications of ANN on economic problems, we decided to leave model selection for further research. Although other methods ANN methods such as Recurrent Neural Networks, Convolutional Neural Networks and many other types of Deep Learning Architectures can be used, we do not expect that their results could be different for simple Forward-looking architecture. We also agree that other machine learning methods such as Support Vector Machines, Random Forests, Clustering analysis, etc., may also offer similar results, but we do not expect that any other method may offers opposite or contradictory results. In saying this, we decided to leave the question of model selection for future research.

In the first part of this work we include some literature on local fiscal deficits as well as the local budget features that are included in the analysis. The second section explains briefly the concept of Artificial Neural Networks. In the third section, we explain the data used for analysis of local public deficits as well as the results of a simple single layer ANN analysis along with a contribution measure obtained for evaluating each chapter of the Municipal budget. The final part of this work contains the conclusions.

Local Fiscal Deficits

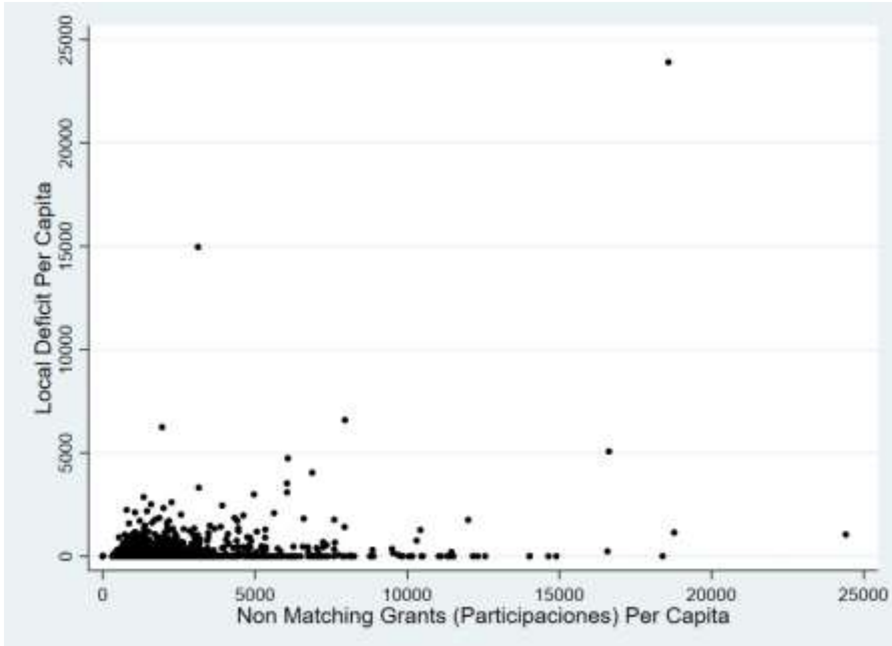
A budget deficit occurs when public expenditures exceed revenues. The deficits at the national level are strongly influenced by the business cycle but also by macroeconomic shocks. It can be thought that the public deficit generates an expansion of aggregate demand in consumption and this leads to a proportional decrease in savings. This causes a lower investment and a lower productive capital. Although in an open economy, the effects of loans to governments to solve their deficits may appear that there is no effect on interest rates, but competition with private savings could lead to a congestion effect and the increase of domestic interest rates. Because we are dealing with local public deficits, the most feasible ways to confront the fiscal deficit may be adjust expenditures or borrow from the private sector (banks) which is now a possibility under the current fiscal rules.

Public debt may also be understood intergenerationally, as a tax burden for future generations who will arrive with a lower stock of capital as Modigliani mentioned in (Modigliani, 1986). Therefore, there are many factors to consider when analyzing public deficits: Tax collection costs, types of taxes and local revenues, income opportunity, tax evasion, time horizon and effects on economic agents, etc. The primary deficit is defined as expenditures minus taxes (revenues): $D = G - T$. The total deficit includes the service of the public debt. In other words, the total deficit is equal to the payment of the debt plus the primary deficit: $DT = rB + G\ T$, where r is the interest rate and B is the accumulated debt in the previous fiscal period. In this paper we will try to estimate the primary local public deficit, which is due to short-term circumstances (annual).

There are 2,448 Municipal governments in Mexico plus another 16 City Boroughs of Mexico City. Each local government collects taxes and receive Federal grants that could be unconditional and conditional. On the side of local governments revenue, we may say the Mexican Municipalities do not have to deal with macroeconomic stabilization and many of the income receipts are stable. However, we must also consider the possible influence of local public revenue on the deficit, especially through local public debt.

Transfers from the Federal government rely on a matching formula and are somehow predictable, accounting for about 80% of local Municipal revenues. Some of the Federal transfers are matching grants which target specific public investment projects, but such grants vary in accordance with a formula that increases revenues for poor Municipalities. On the other hand, there are unconditional grants that may be used for general expenses, which are increasing with Municipality mean income and fiscal effort. Despite a stable source of local revenue, it is hard to predict which chapter of the municipal budget is more likely to be adjusted for unexpected local government expenditures.

Figure 1: Local Deficits and Non Matching Grants 2015



In Mexico, the capacity to cut certain municipal expenses or increase local revenue are both of limited use. For example Sour, (2009) found some evidence to show that the introduction of unconditional grants (general purpose grants) support the hypothesis of *fly paper effect* with political competition, explaining the increase (decrease) on unconditional grants, which may in turn decrease (increase) local deficits through local public debt. Also Díaz González, Jaime, and Del Roćio, (2017) found evidence to support the *fly paper effect* hypothesis in Mexico. Other research that supports the idea of political influence in local public debt financing is Benton and Smith, 2014) and similarly Smith, (2015) which offer policy recommendations for local debt management.

There is little evidence that deficit is caused by economic inequalities. For example, a linear regression on deficit using several explanatory variables such as the Gini Index, Poverty index, Human Development Index, income, and other fiscal variables such as conditional (matching) and unconditional grants was no significant for all except unconditional grants. That is, local deficit seems to be higher as unconditional grants increase (called *Participaciones* or row 28 of the Federal Budget). For example, looking at Figure 1, we may see that the local deficit per capita might be correlated positively but barely. Indeed the R^2 of the regression was just 0.068, not enough to justify a good fit. This means that usual Least Squares regression has serious problems of endogeneity and heteroskedasticity caused possibly by complete causality and determinism. Therefore nonparametric methods can be more useful to deal with the problem at hand.

Despite the fact there are obvious connections among some chapters of the revenue side of the Municipal budgets, we decided to concentrate on the expenditure side of the Municipal budgets in Mexico. Local debt servicing will include the indirect effect of some revenue chapters such as unconditional grants, as suggested by (Sour, 2009). The chapters in each Municipal budget in the expenditure side are:

- Personal Services. This accounts for wages and salaries to all workers in the Municipal administration as well as services paid for contractors.
- General Services. This contains all expenses for activities related to Municipal work and programs.
- Office equipment and buildings.
- Office supplies and consumables.
- Debt payments and servicing, mostly to commercial banks.
- Transfers and subsidies.
- Public investment in infrastructure and social programs.

The more practical question is how to start an empirical analysis on the Municipal budget. The common practice might be to use the usual Parametric techniques available but given the nature of the data this means that we must overcome natural endogeneity and the lack of clear causality. Therefore, we decided to test with other types of statistical methods. A possible parametric approach could be the use of dynamic panel regression analysis, which may require a large data set that may include the time dimension. We decided to explore parametric methods for a future research, as our main aim is to show that nonparametric methods can also be useful even with small data sets.

After a review of several possible methods, we decided to use ANN to forecast local fiscal deficits using the chapters in the expenditure side of every Municipal Budget. Once the best possible prediction has been made, we may use the network weights to infer on the importance of each of these features and offer some results.

Artificial Neural Networks

The history of Artificial Neural Networks began in the 1940's but it was until early 1960's that the idea that machines can learn was first explored with the creation of the Perceptron Algorithm. Although there were great expectations on artificial intelligence, the computer technology was not well advanced at that time to make artificial neural network to work in their full potential. A big leap forward in ANN research was PJ Werbos (1974) unpublished PhD Dissertation "Beyond regression: new tools for prediction and analysis in the behavioral sciences", where he first proposed *Backpropagation* to train Neural Networks. A detailed explanation on Backpropagation can be found also in (Werbos, 1990). Backpropagation algorithm was indeed a break-through that allowed the effective use of gradient descent method in the training of ANN.

There have been numerous efforts to design artificial neural networks based on Von Neumann's architecture, trying to produce intelligent algorithms that mimic biological neural networks. Neurons are very special cells in the human brain that are interconnected with each other and respond to stimuli using chemical and electric reactions with connections called synapses. The idea of ANN is to simulate neurons stimuli process and let these neurons to learn by themselves controlling the information (stimuli) which is passed on to the next neurons. In this way we can create an Artificial Neural Networks (ANN) where the nodes are considered neurons and its weights say how much stimuli are needed to predict an outcome.

Though several versions of ANN have been developed, the backbone behind all architectures continue to be the gradient descent method used in Feedforward and Backpropagation algorithms. ANN can perform complex classification problems but for a simple binary classification, the idea is to use a decision function $h(x)$ to approximate the outcome or label $\boldsymbol{y}$ which is binary in our problem, either zero if there is no local fiscal deficit or one is there is a deficit. The decision can be made a simple weighted function of a linear combination of features:

$$h(\mathbf{x}; \theta, b) = \theta^T \mathbf{x} + b \qquad (1)$$

The main objective is to find the weights θ and the parameter b (bias) that may be used to describe and predict the outcome $\boldsymbol{y}$. As mentioned before, a neural process is a biological process that describes how a neural cell learns. A neural cell processes information from stimuli it receives and then uses a series of synapses to pass on new information already processed to another cells. An ANN tries to reproduce the same process, using inputs nodes to receive information, one or more hidden layers to process the information using an activation function in each artificial neuron, and then output nodes where the processed information is received. Given an output $\boldsymbol{y}$ we must train our network to *learn* and obtain these output values by iteration. At the end, the weights θ will be obtained and will be used for prediction.

The process of training an ANN will depend on the activation function we want to use as well as the method to find the appropriate weights recursively. We use Gradient descend iteration in a Backpropagation network. Usually, we may initiate to train the ANN with random input values and then apply weights to every data point that will pass on information to a hidden layer where the information will be processed by an activation function. Weights are recalculated iteratively until convergence is achieved. We cannot work in an ANN where the values in the decision function are extremely small or too large. This problem will lead to low speed or even failure of the network. It is desirable that the values we get from the decision function $h(\mathbf{x}; \theta, b)$ being in a small range, for example, between 0 and 1. One way to achieve this is to map the decision function $h(\mathbf{x}; \theta, b)$ into a new function what will give an output between 0 and 1:

$$h(\mathbf{x}; \theta, b) = g(\theta^T \mathbf{x} + b) \qquad (2)$$

To represent g as a new function of $\mathbf{z}(\mathbf{x}) = \theta^T \mathbf{x}+b$, we may start to use a sigmoid function of the type (although there are other types of functions that may be useful to represent g):

$$g(z) = \frac{1}{1+ e^{-z}} \qquad (3)$$

This is akin to a logistic regression function with $g(\mathbf{z}) \in [0, 1]$. This is called an *activation* *function* because this function will process the information and put forward an output. This activation function will process the data in every neuron, in every hidden layer of the neural network.

The decision function will approximate the label $h(\mathbf{x}^{(i)};\theta, b)\ y^{(i)}$ for every data point $i = 1, ..., n$. The idea is to use all the past data to learn the values θ, b and to approximate the values of $\boldsymbol{y}$. We may try to minimize the sum of square errors as our *objective function* or *loss function* as follows:

$$H(\theta, b) = \sum_{i=1}^{n}(h(\mathbf{x}^{(i)}; \theta, b) - y^{(i)})^2 \qquad (4)$$

The crucial step in is to minimize 4 above which is the same as to minimize the error function $(h(\mathbf{x}^{(i)};\theta, b)\ y^{(i)})^2$. The main task will be to obtain the parameters θ and b in such way that the error is minimized. One optimization technique is to use iteration in order to approach to the optimum values of θ and b. One optimization method is called the *stochastic gradient descent* algorithm. The stochastic gradient descent algorithm allows to learn the decision function $h(\mathbf{x};\theta, b)$ computing the above gradients by iteration. The gradient descent algorithm is a key feature of the ANN. The use of the gradient descend method will integrated in the *backpropagation algorithm* (BP), which collects the logical steps for the learning process using a backward pass. This backward pass will refine the weights until no better outcome can be improved. The gradient descent method iterates the following recursive formulas:

$$\theta_i = \theta_i + \alpha\Delta\theta_i$$

$$b = b + \alpha\Delta b$$

Where the θ_i are the weights of the network and b is the bias. The $\Delta\theta_i$ and Δb are the gradients which amount for a small amount of adjustment through the network. And the α is the learning rate which may say how much the network can learn and how fast we descent through the objective function we supposed to minimize.

The Empirical Analysis

We collected local public finance data for 2135 Municipalities for the year 2016, published by the INEGI, for all the chapters of the expenditure side of the Municipal budgets. We also collected data on those municipalities that fell into fiscal deficit in the fiscal year 2016. Then, we constructed a label using a dummy where a zero describes a Municipality with no deficit and one is a Municipality with a substantial deficit. From the standard statistics of table 1 we may see that about 44% of Municipalities were in some deficit in 2016. Accounting deficits of few hundreds of pesos were not considered fiscal deficits, because they are surely due to accounting problems.

After constructing the main data set all variables were normalized in values between zero and one, in order to avoid undue influences of usually large amounts as in the chapter of Personal Services. Then a training data set was constructed using 70% of the Municipalities and the remaining 30% was used for testing and prediction (test data set). The rule 70:30 used here is very standard in the literature (e.g. (Kim, 2003)) though we may change these ratios at will to observe how much improvement in prediction is gained due to a larger training set. Because we are not dealing with time series data, where the order of the observations is important, we must choose our training and test sets randomly.

Table 1: Standard Statistics: Mexican Municipal Public Expenses 2016

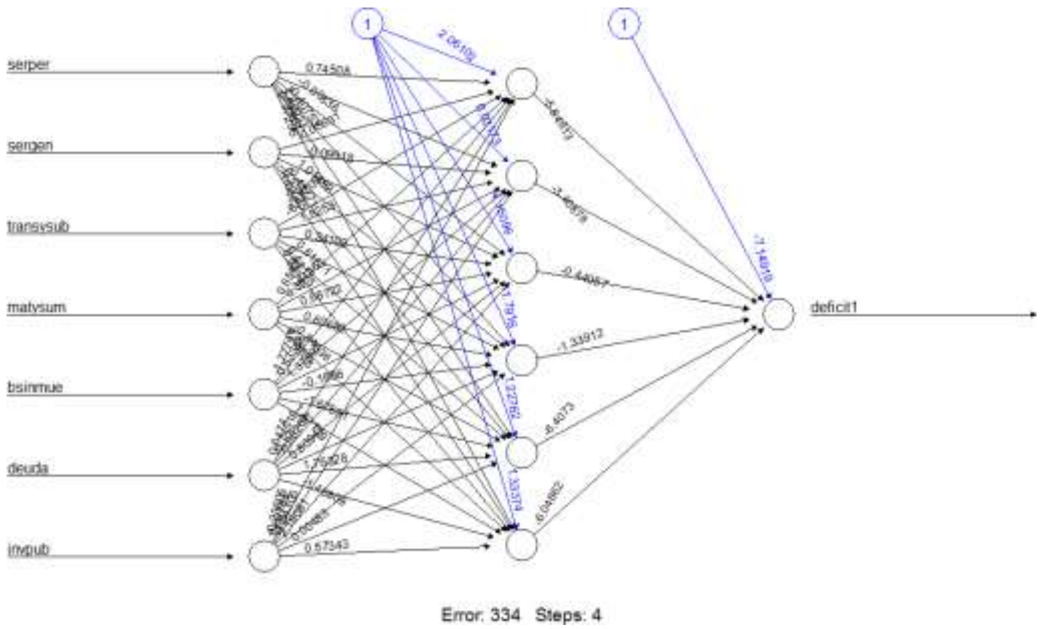
Variable	Obs	Mean	Std. Dev.	Min	Max
Deficit	2135	0.4430913	0.4968672	0	1
Personal Services	2135	6.60E+07	2.16E+08	0	3.58E+09
General Services	2135	2.92E+07	9.13E+07	346732	1.34E+09
Transfers and Subsidies	2135	1.70E+07	7.11E+07	0	1.28E+09
Office material	2135	1.33E+07	3.28E+07	90766	6.41E+08
Buildings	2135	3092719	1.08E+07	0	2.02E+08
Debt	2135	6814829	3.46E+07	0	8.53E+08
Public Investment	2135	4.48E+07	9.12E+07	0	1.62E+09

The usual architecture for prediction of economic and financial data are Forward-looking artificial networks. We did not use complex looping and other architectures. Backpropagation ensures that weights are also updated using a backward pass during the learning process. After several trials we decided for a learning rate of 0.1, as this rendered the best prediction. A simple architecture of 6 neurons and one hidden layer was constructed and performed for prediction.

Then a hit ratio was constructed to see how many times a deficit was successfully predicted, using the predicted values of the network and the real test data. The hit ratio for a 6-nodes architecture was 0.5663026521, which means that using the above features we were able to predict with a probability of 56.63% if a Municipality will fall into deficit. Other architectures were also tried using more neurons and additional hidden layers, but still the 6 nodes with one hidden layer performed better. For example, a 12 nodes network rendered a hit ratio of 0.4336973479, which decreased prediction. An increase on the number of nodes and layers not always improve prediction, for an example of this see (Gallardo Del Angel, 2020). The simple 6-nodes networks used in this analysis is shown in Figure 2.

As in many other Machine Learning methods with supervised learning, the more and better data is provided the better is the prediction. The important question in this method is to find the global minimum in our loss function, repeating by iteration using initial random weights. The implementation of Backpropagation algorithm was done using the package *neuralnet* in R. Although this package was constructed to implement Resilient Backpropagation Neural Networks, simple Backpropagation is also possible using this tool. For an example of Resilient and the usual Backpropagation Neural Networks applied to financial data see (Gallardo Del Angel, 2020). Improvements are little using different algorithms with different architectures because we are using the same data set. We therefore opted for a simple network to obtain straightforward results.

Figure 2: ANN with 6-nodes on Municipal Expenditure data



However. our objective is not prediction itself, rather we are interested in the relative importance of the feature variables. The main objective of this work is not only about forecasting but evaluating the overall performance of the features used for prediction which, as mentioned before, we do not expect to vary a lot with other methods. This is an important objective because it gives us information on the relative relevance of each feature in the learning process. Because each feature is normalized, each weight offers relative information respect to others. We can use the weights to find out which of each feature have more influence in the network.

We estimated each contribution measure on the best 6-nodes neural network. If the input layer has $i = 1, 2, ...I$ nodes, and the hidden layer has $j = 1, 2, ..., J$ neurons, the final output weights will come from equal number of nodes $k = 1, 2, ..., J$. We use the measure called Garson measure as in (Huang, Chen, Hsu, Chen, and Wu, 2004):

$$GC = \frac{\sum_{j=1}^{J} \frac{|w_{ji}||v_{jk}|}{\sum_{i=1}^{I}}}{\sum_{i=1}^{I} \sum_{j=1}^{J} \frac{|w_{ji}||v_{jk}|}{\sum_{i=1}^{I} |w_{ji}|}}$$

The Garson measure is a kind of weighted average, and can be put into percentages to have a better understanding of the relative relevance of each feature. The contribution measure for each feature is shown in table 2. The Garson contribution measure shows that from all chapters of the Municipal budget, local public investment has the lowest influence in the network. Because the analysis of the Municipal budget is certainly very deterministic, we were expecting similar influence from all chapters into the deficit. Rental of buildings and vehicles, local public debt payments and personal services are the most influential variables in the prediction of the local fiscal deficit.

Conclusions

This paper raises the question of what kind of expending behavior is inducing the local public deficits in Mexico. Little evidence can be found to support the idea that economic and regional problems are causing the deficits at Municipal level. Some argue that unconditional grants might be related to the deficits on the local revenue side. That political factors are also important to be considered for debt financing and management. But there is still the question of what kind of expenses are driving the local public deficits. We decided to look in the expenditure side of the budget to see if there is any anomaly in the way Municipalities are behaving.

Table 2: Contribution Measure: Mexican Municipal Public Expenses 2016

Feature	Garson Measure
Buildings	17.2%
Debt Servicing	16.9%
Public Investment	7.7%
Office Material	14.3%
General Services	12.2%
Personal Services	16.5%
Transfers and subsidies	15.1%

To answer the previous question we decided to use machine learning methods, specifically Artificial Neural Networks, in order to predict Municipal fiscal deficits and obtain weights that can used to evaluate the information from the network. We used the chapters in the expenditure side of the Municipal budgets in order to predict local deficits. Those chapters can be grouped in two broad categories: current expenditure and investment expenditure. The first includes all kind of operational expenditures such as wages, office equipment, building rental, machinery, public utilities, personal services, service contractors, etc. The second group comprises local public investment expenditure which includes building infrastructure, social programs such as health services and education, etc. The first group of expenses are related to the managerial capacity of each Municipality while the second group of expenditures is related to the provision of local public goods and capital formation in each Municipality. The main results show that operational and current expenditures are driving the local fiscal deficits. This is puzzling because we expected that provision of local public goods could be the leading cause behind local deficits, but it is not.

We know that the main priority of local governments is to provide with a wide range of local public goods, so we expected local public investment could be a strong driver behind deficits. A possible answer to this lack of importance on the side of local public investment could be the deterministic rules that guide conditional (matching) grants. Another causes could also be the lack of accounting rules or poor management. Whatever the reason behind the local deficits, our results show that all current expenditures are extremely relevant and provides the most information in the network. Local public investment is almost not relevant at all. This is somehow expected and reasonable because conditional (Matching) grants, which is the main source for local public investment, are strictly supervised and designed to achieve a preset of goals. On the other side, unconditional grants are more flexible and compensate Municipalities for their tax effort, allowing them to use these resources for any eventuality. The main conclusion is that local public deficits in Mexico are driven by current and operational expenditures that have to do with management decisions. If local public deficits cannot be justified by social investment, it is hardly probable that new taxes can be used as a justification for local public investment.

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