The impact of mining taxes on public education: evidence for mining municipalities in Chile

Mauricio Oyarzo[§]
Department of Economics, Universidad Católica del Norte, Chile
moyarzo@ucn.cl

Dusan Paredes
Department of Economics, Universidad Católica del Norte, Chile
dparedes@ucn.cl

Abstract

Chilean mining municipalities collect a mineral tax to compensate the negative externalities associated with resource extraction. This collection implies a positive marginal impact on local finance to improve the quality of life in the mining communities. However, there is not enough empirical evidence to support this causal mechanism. This article contributes to cover this knowledge gap with a unique experimental framework proposed by the Chilean tax system. In particular, mining law indicates that municipalities above an exogenous threshold are able to keep this extra income. We use this Regression Discontinuity Design to identify the causal effect in public education indicators of the mining communities. Our results show that the mining municipalities these have a worse educational performance. In addition, the levels of spending in public education are not significant, which accounts for the disadvantaged position in relation to the high dependence on extractive activities.

Keywords: Public education, Mining taxes, Public education, Local governments.

JEL Classification: H20, H40, H70, H32, H34, I25.

[§] Corresponding author.

1. Introduction

Mining tax legislation obliges monetary compensation from the extractive industry in order to counteract for the negative externalities that arise from the production and exploitation of a nonrenewable natural resource (Hughes, 1975; Ergas & Pincus, 2014). This compensation constitutes an additional income for mining municipalities without necessarily entailing a greater tax burden on its inhabitants (Stinson, 1977). However, there is little evidence regarding the impact of said income on the well-being of these local communities, and in particular their public education. The formation of human capital drives the diversification of productive activities and is essential for handling the ebbs of flows of commodity prices in communities that are highly dependent on extractive activities (Emerson, 1982, Andrews-Speed & Rogers, 1999).

Even though literature is scarce, there are articles that acknowledge that extra tax revenue from extractive activities does not always result in an increase in the provision of public goods. Dobra & Dobra (2013) and Rivera & Paredes (2016a) indicate that this extra revenue not only diminishes local efforts to collect other taxes (it would entail a greater social-political cost) but that municipalities are also inefficient in the management of resources despite the extra income they receive (Brollo et al., 2013). The literature also suggests that given the peripheral condition of these communities, they will generally have lower human capital, which negatively affects the efficiency in local public administrations as well as the quality of the public goods provided (Bjorvatn et al., 2012).

Therefore, it is important to evaluate whether mining taxes result in a better provision of public goods, with special emphasis on those that affect the quality of life of local society. Given the complexity of representing public education, as well as the lack of information available at the municipal level, this paper proposes to use two indicators which will quantify both the investment in and the quality of public education. Quality is approximated via the percentage of students from public schools that score higher than 450 points on the University Selection Test (PSU).[i] Investment, meanwhile, takes into consideration the percentage of municipal public spending on education and determines whether the mining tax is actually spent on education.

In order to carry out this analysis we use Chile, one of the principal mining countries in the world, as a case study. The country's mining tax collection mechanism offers an ideal quasi-experimental scenario that will allow us to evaluate impact at a municipal level.[ii] According to the Chilean Law 19,143 regarding Mining Patents, the resources collected are distributed as follows: 50% to the mining region and 50% to the municipality in which the concession is located, granted that it is classified as a *mining municipality*. A municipality must satisfy two conditions in order to be categorized as a mining municipality: at least 2.5% of the region's total revenue must come from mining activity; at least 2.5% of the local municipality's total revenue or its *Ingresos Propios Permanentes* (IPP) must come from mining permits. If the municipality does not satisfy both conditions, then it is automatically a control and it does not receive any extra income.[iii] Treated municipalities therefore have an extra income, which allows a marginal comparison of their performance in public education indicators under an exogenous allocation rule, which makes it possible to exploit an impact evaluation design through Regression Discontinuity Design (RDD) (Lee & Lemieux, 2010). All municipalities at or around the 2.5% cutoff point are classified as treated and as almost random (quasi-experiment) controls, which is an ideal scenario for assessing impact (Dahlberg et al., 2008).

This research utilizes a database of 345 Chilean municipalities, which corresponds to a total of 2,102 observations for the period between 2010 and 2016. The municipalities under consideration are classified into one of three groups: 1) 405 mining municipalities (treatment group), 2) 1,007 non-mining municipalities within non-mining regions (strong control group) and 462 non-mining municipalities within mining regions (weak control group).[iv] In order to reduce the potential spatial autocorrelation of the variables under study, geographic distance controls are included among municipalities in order to rule out spillover effects among spatially close neighbors.[v]

For the period analyzed, the results show lower educational results for mining municipalities as compared to the strong and weak controls. The impact of the extra income from mining patents on the PSU percentage is negative and significant, ranging from 38% to 21%. In terms of spending on public education, although mining municipalities allocate a smaller percentage of resources, in the margin the difference is not significant. The difference is significant, however, when we use geographical controls at around CLP $33 million pesos (US$50 thousand). The results show that, in spite of the higher incomes of mining municipalities, there is no clear improvement in the investment in or quality of local public education.

This article is divided into six sections. Section 2 presents the literature review while section 3 explores the data. Section 4 presents the methodology used to evaluate the impact. Section 5 describes the main results and section 6 discusses the implications and concludes.

2. Literature Review

The relationship between the extra income from extractive activities and the provision of public education has been addressed indirectly through the resource curse hypothesis. This hypothesis refers to the negative relationship between natural resources and indicators of economic growth, and public investment in education has been a leading subject of analysis (Hong, 2014, Zhuang & Zhang, 2016, Dettman & Pepinsky, 2016).

The literature indicates that localities with high levels of natural resources develop a false sense of security and economic stability due to the extra income in boom times. This discourages the need to create strategies that promote economic growth, such as investment in non-technical public education (Douangngeune, Hayami & Godo, 2005). Annabi, Harvey & Lan (2011) indicate that the impact of said investment on the accumulation of human capital depends on alternative fiscal instruments and the efficiency of public spending on education. The precariousness of the income from extractive activities results in inefficient fiscal planning which translates into peaks and troughs in public spending (Lane, 2003; van der Ploeg & Poelhekke, 2009).

The disincentive to invest in education is also a relevant characteristic of mining areas. The demand for skilled labor is sensitive to the type of predominant economic activity, and therefore conditioned in those localities with a high level of natural resources (Shao & Yang, 2014). Labor markets with mining present consist mainly of a small proportion of highly skilled workers, such as engineers, and a large proportion of medium skilled workers in operational activities (Gylfason, 2001). Therefore, the incentives necessary to invest in education are lacking, which limits the possibilities of diversifying the economy and subsequently to cope with periods of economic crisis. The literature confirms the lower level of investment in education in mining areas and the low incentive of local governments to actually convert such investment into something tangible, since the results are more perceptible over the long term. In addition, the sources of economic income are less dependent on the educational level of the population, which reinforces the disincentive of local governments to invest and therefore potentially handicaps the development of local human capital.

The empirical results of the impact of extra income on the provision of education are ambiguous and depend on context and place. In the case of the United States, Michaels (2011), when comparing areas with a high production level in oil extraction with other (less specialized) areas found no significant differences. This means that the high level of production does not influence the provision of education. On the other hand, Olson & Valsecchini (2012) employ a Regression Discontinuity Design (RDD) and report a positive impact on the provision of infrastructure in secondary education in Indonesia, where the abundance of natural resources benefits extractive localities. This is also true for the case of Iran (Mahdavi, 2012), where provinces with a greater amount of resources also have a higher provision of education, something that does not change over the period analyzed.

In the case of China, Zhuang & Zhang (2016) suggest that local governments tend to invest a smaller amount of resources in social spending, specifically in public education. Hong (2016) also finds negative results for China and traces it to the negative relationship between the provision of public education and the level of production. In Indonesia the scenario is no different. Dettman & Pepinsky (2016) find that public spending on education is not a significant element in areas that specialize in extractive activity. Regarding the ambiguous results, it can be inferred that they might be due to the type of extractive activity and to the administrative context of the units in comparison.

For Chile, Rivera & Paredes (2016b) utilize an impact assessment design by using instrumental variables (IV) in order to measure the impact of mining patents on four indicators of local public goods. The authors find that mining taxes increase the provision of public goods in mining municipalities. However, they do not explicitly consider any indicator for local public education, an aspect that directly affects the welfare level of a large part of the population and which municipalities have a greater capacity for decision-making in the administration of resources.

This work is a contribution to the aforementioned literature in at least three aspects. First, it directly addresses the relationship between the extra income derived from extractive activities on indicators for spending and efficiency in regards to public education. Second, it improves what has been developed by Rivera & Paredes (2016b) as it includes the provision of local education as an indicator of public goods. This is a segment in Chile that municipalities have a greater degree of influence in regards to investment decisions.

Finally, an ideal quasi-experimental design of impact assessment is used, which employs the discontinuity of total local income as a result of the exogenous allocation of mining *municipalities* as a treatment group, and its comparison with non-mining municipalities or control groups. This increases the possibility of finding causal results in educational variables that show no linearity. This work is therefore an interesting contribution to the empirical literature, since most of the previous works' estimates suffer from problems of endogeneity, which hinders you from obtaining causal results. We also contribute to reducing the knowledge gap in countries with a high presence of natural resources, where mining plays a central role in the level of local development, and where little regarding the efficient allocation of compensation mechanisms and the fulfillment of public policy objectives has been discussed.

3. Data

3.1 Dependent Variables

This research considers information obtained from the National Municipal Information System (SINIM) for 345 municipalities.[vi] For the period between 2010 and 2016 this involves having 2,102 observations (treated and controls). Table 1 presents the details of both of these groups according to the institutional criteria established to denote mining regions and, consequently, mining municipalities. According to the table, the treated group presents a low variability since the number of mining municipalities decreases from 59 in 2010 to 56 in 2016. This implies a total of 405 mining municipalities for the entire period.[vii]

<<Insert Table 1 here>>

Meanwhile, two control groups (strong and weak) are built. The first has a greater degree of variability in the number of observations and corresponds to non-mining municipalities in non-mining regions. There are 128 non-mining municipalities in 2010 and 183 in 2016 and they account for 1,007 observations. This group is constituted as the strong control since the municipalities do not receive extra income from mining taxes. The second control group is formed by non-mining municipalities in mining regions. Similar to the treated group, this group represents a low degree of variability in the number of observations. The controls in this category number 66 municipalities in 2010 and 75 in 2016 while the total number of non-mining municipalities is 465. This group is constituted as weak since it indirectly receives part of the mining taxes through governmental transfers at the regional level (50% of the revenue of the mining patents in the mining region).

It should be noted that there is a fourth group of 225 municipalities that, despite being listed as mining municipalities, belong to non-mining regions, and therefore do not meet the requirements to be established as a counterfactual.[viii] In order to take advantage of the data set in the study period and considering the constraints imposed by the method of impact evaluation (in that it is not developed for panel data), we opt to work with a data pool. This implies taking the respective precautions in the interpretation of the results. However, it also means evaluating the impact year by year (which are reported in appendices that can requested from the authors).

After defining the treatments and controls, we proceed to define the dependent variables on which impact is evaluated. Municipal public spending on education is defined as the first dependent variable and corresponds to its own financial contribution to the public education sector together with any support from the Ministry of Education. If mining municipalities have a surplus in income, then it's possible it will be allocated to public education in order to improve local indicators. However, this variable does not measure effectiveness and only refers to the allocated budget amount that comes from the governmental and local sources.

The second dependent variable corresponds to the percentage of local (municipal) students with University Selection Test (PSU) scores greater than or equal to 450 points, which corresponds to the minimum score necessary for accessing the Chilean university system.[ix] It should be noted that this variable does not consider what is actually spent on education, but rather points to the effectiveness of the system. In this case, effectiveness is key, since the PSU score is a crucial factor for students applying to the university system. Additionally, the Chilean Congress is currently discussing education reform and so the variable is highly relevant. However, the limitations imposed by a variable that does not necessarily reflect the effectiveness of the extra income in the long-term are recognized, and so any interpretation of the results should be done with caution.

The proxies for the use and effectiveness of the extra income represent the work that municipalities do in regards to the management of these resources. Line items include school and facility infrastructure and personnel (teachers) and support staff, among other things. Although these variables are not the only indicators, they are the best proxies given the constraints of information available at the municipal level. Table 2 shows the descriptive statistics of both variables by treatment group and controls.

<<Insert Table 2 here>>

According to Table 2, the average expenditure for the treated group on public education is CLP $30,836 million (US$46 thousand), which is below the averages for the counterfactuals, the strong group average being CLP $57,837 million (US$89 thousand) and the weak group CLP $54,080 million (US$83 thousand). In addition, the treated group has a wider confidence interval than the counterfactual ones, reflecting a greater degree of variability in the sample. However, such a comparison may have a high degree of error when considering all observations. This is corrected in part by assessing impact via RDD and by considering only those observations that are in the general vicinity of the cutoff point. This also allows us to reveal significant differences between the treated and counterfactual groups.

The second dependent variable corresponds to the percentage of students with PSU scores that are greater than or equal to 450 points. Both control groups exceed, on average, the treated group, with the strong control group standing out with a rate of 41% and with a lower level of fluctuation according to the confidence interval. The second control group also outperforms the treated group by about 5%. As shown in Table 2, the mining municipalities start with a lower rate for the PSU variable. It is therefore important to evaluate whether this difference can be shortened after the applied treatment. In summary, mining municipalities are not able to invest more money in education than the counterfactuals, which is also evident when considering PSU scores, since in no case do the counterfactuals match the controls. To extend this analysis, Figure 1 presents the averages and confidence intervals for the dependent variables in the different years.

<<Insert Figure 1 here>>

In both graphs, for both education spending and PSU performance, the difference in the averages for the treated group and the controls remained stable during the period, which is captured by considering the aggregate for the last three bars. Therefore, the trends support the idea of evaluating the impact for the period in a context of pool data, which increases the degrees of freedom in RDD, although it's necessary to take the respective precautions when interpreting the results.

3.2 Explanatory variables

The first explanatory variable used to evaluate impact corresponds to the percentage of the revenue from mining patents over the IPPs (the total municipal revenue) of the municipalities under analysis. This variable represents the discontinuity that occurs at the cutoff point when they are compared to municipalities that are in a vicinity of 2.5% and establishes the treated and counterfactual conditions. This variable is, undoubtedly, the most interesting control for research. For example, for 2010 there are 59 mining municipalities (they fulfill both questions) located in 9 regions of Chile: Arica, Parinacota, Antofagasta, Atacama, Coquimbo, Valparaíso, O'Higgins, Aysén and Magallanes. For this particular year, the map of mining municipalities and controls is detailed in Figure 2.

<<Insert Figure 2 here>>

The second explanatory variable used is the municipality's own income or *Ingreso Propio* (IP). These revenues are generated autonomously in each municipality via territorial tax, commercial patents, traffic permits as well as the Municipal Common Fund (FCM). This variable allows to remove the effect of the autonomous income with respect to the government transfers that are contained in the dependent variable for spending in municipal education. This variable is also relevant for PSU scores since it potentially influences the performance of public school students by providing greater resources to the education system.

We also consider controls for economies of scale in the provision of public goods via municipal population, which accounts for the asymmetry in the distribution of the population in Chile. To isolate the impact of mining patents on spending and academic performance, controls for municipal public school staffing and infrastructure are integrated. This includes the percentage of teachers per student, the average monthly enrollment and the number of public schools for urban and rural localities. Finally, in order to partly capture the level of access to public goods in the treated municipalities, a control for the municipal poverty index is included, which is constructed using information reported by the National Socioeconomic Characterization Survey (CASEN).

The descriptive statistics of the explanatory variables are presented in Table 3. As expected, the average participation of the mining patents in the IPP is significantly higher for the treated group: the rate is 28% and it fluctuates around 5%. Meanwhile, the control group rate is below 1%. These results partially validate the discontinuity at 2.5%, which is the ideal scenario for evaluating the impact in RDD.

<<Insert Table 3 here>>

On the other hand, the treated municipalities present, on average, a smaller amount of potential users of public goods. Specifically, the average for the treated group corresponds to 26,908 people and is below both counterfactuals by almost 50%. Regarding the IP, it is notable that the treated municipalities have a lower level of revenue (CLP $4 million, US$6 thousand) compared to the control groups (CLP $7 million, US$11 thousand for the strong and 6 million, US$9 thousand for the weak). Regarding the variables that correspond to the teaching staff, enrollment and infrastructure, it is important to note that in each item the treated group is below the controls that are considered, which undoubtedly affects the results in terms of the spending and effectiveness of the mining taxes. Finally, the indicator for municipal poverty is lower for the mining municipalities, which are on average 6% below the strong controls (20%). The weak controls report an indicator close to 14%, which is quite similar to treatment.

4. Methodology

As discussed earlier, this work uses a Regression Discontinuity Design (RDD) to exploit the discontinuity generated by the government regulation in the allocation of taxes. Unfortunately, there is still no data panel version for RDD. This is why we proceed to estimate using a pool of data despite the discrepancy in the number of observations in the treated and control groups in the period under analysis. Discrepancies can be smoothed by adding the figures in the 7 years under study. Consider the following model:

$$Y = D\tau + W\delta_1 + U \quad (1)$$

$$D = 1[X \geq c]$$

$$X = W\delta_2 + V$$

Where Y is the dependent variable, D is the binary variable that indicates if it exceeds a cutoff point corresponding to c≥ 2.5%, W is the vector for all predetermined variables and observable characteristics that can impact the dependent variable and/or allocation variable X, considering for this aspect the municipal population and other controls. U and V represent random error terms. A linear regression would return a biased coefficient (τ) because it assumes linearity of the variable under analysis, it would also include all the units under study and the treated and control group assignation is non-random. On the other hand, if the analysis is limited to only those observations in the vicinity of the 2.5% cutoff point, we would have a random experiment in which the absence of linearity would allow us to calculate the impact on the margin, i.e. where the treated and counterfactual are comparable.

This provides a valuable means of establishing a causal relationship between D and Y (1) close to the cutoff point. Therefore, two groups are generated, those that obtain a score of 2.5% or higher according to c (treated group) and those that are below the cutoff point (control group). It is therefore possible to compare both groups and to determine if the treatment effect on the treated, better known as the Treatment Over Treated (TOT) was effective by evaluating the level of municipal spending on public education as well as the municipal educational results (PSU results).

In order to apply RDD certain criteria must be met, namely, discontinuity validation and group differences. To validate the discontinuity, the units of analysis should not be able to alter the variable that determines the treatment allocation, which in this case corresponds to the percentage of mining patents over IPP. This is validated in the sense that the classification of municipalities as a treated group obeys an exogenous rule (the institutional framework) in which municipalities cannot be re-categorized.

Finally, the choice of bandwidth in RDD can have a direct effect on both the variance and possibly also introduce bias into the regression. Larger bandwidths tend to reduce variance but they also allow for bias in the estimates due to the greater number of observations. On the other hand, lower bandwidths tend to reduce bias, but may increase standard errors due to the lower number of observations. For our estimations, we use various bandwidth methods according to Calonico, Cattaneo, Farrell & Titiunik (2016a, 2016b), which either minimize the mean squared error (MSE) or otherwise minimize the coverage error rate (CER) on both sides of the cutoff point. However, we only report the estimates for the MSE. The CER results can be requested from the authors.

To evaluate the impact, two RDD methods are used. The first is a local linear regression model, in which observations from within the immediate vicinity of the discontinuity will be used via a chosen bandwidth. The model is specified as follows:

$$Y_i = \theta\gamma_i + \epsilon_i \tag{2}$$

Where γ is a dummy variable that indicates the allocation of the treatment. θ provides the TOT and will show how going over the cutoff point of 2.5% alters municipal spending or educational results in mining municipalities. Different methods of RDD including conventional, bias correction and robust are estimated. The first and second methods estimate variance in a conventional way without correcting for heteroscedasticity problems, while the third method corrects the problem and reports robust standard errors.

The second method uses polynomials and will include both observations close to the discontinuity, but also the more distant ones. The model is specified as follows:

$$Y_i = \theta\gamma_i + \beta_1\Gamma^2 + \cdots + \beta_n\Gamma^{n+1} + \epsilon_i \tag{3}$$

Where Γ represents a continuous form of the allocation variable, which for this case corresponds to the percentage of mining patents in IPP. The inclusion of a n degree polynomial can help to absorb the variation of the observations that are far from the discontinuity. This method can therefore provide a more powerful test than a local linear analysis, since it is able to use more observations. However, it can increase bias despite employing a higher-grade polynomial. To deal with this, we include estimates by varying the polynomial used and then test the robustness of the results. Both methods (equations 2 and 3) are included in order to evaluate the impact of mining taxes on educational spending and results.

To control for potential spatial autocorrelation in the dependent variables, controls for the geographical distance between the municipalities are included. This aims to remove control group municipalities that are within a certain radius of kilometers from the treated group. Arbitrary distances between 50 km and 200 km have been defined with a delta of 50 km.

5. Results

Table 4 presents the results that correspond to the estimation of equation 2 in the vicinity of the cutoff point with a 1st degree polynomial. We expect that mining municipalities that receive the extra income will have better results (higher spending and higher PSU scores) when compared to the counterfactuals that are near the cutoff point. However, impact near 0 is also a result of interest for this research, since it can account for a reduction of territorial and consequently, municipal disparities in educational variables.

<<Insert Table 4 here>>

The impacts on public education spending for both strong and weak controls are not statistically significant when considering conventional and robust estimators. The absence of impact does not necessarily imply a reduction of gaps between municipal administrations, but it may be hiding a poor use of public resources, corruption or even the embezzlement of funds. Unfortunately, we are unable to validate these hypotheses with the data available and so they will have to be the subject of future analysis. There is a negative and significant impact on education results measured by PSU scores, which means that both municipalities spatially close to and far from the mines have a higher percentage of students with PSU scores that allow them to access university education. When considering the strong controls that do not receive the income from mining patents, the impact is around 35%. Now, when considering the weak controls, impact falls by approximately 15% which again accounts for a lower PSU score in mining municipalities as compared to their neighbors who do not directly receive extra income.

Table 5 presents the results of equation 3 for public education spending. By considering 2nd, 3rd and 4th degree polynomials we can increase the number of observations in which the impact is calculated and therefore include neighbors further away from the cutoff point. However, as noted in the methodological section, increasing the degree of the polynomial implies an increase in the bias in the estimation of the effect since it considers the comparison of municipalities far from the cutoff point, although they are weighted in order to capture the relevance that they have in the sample.

<<Insert Table 5 here>>

The impact of spending on education considering robust estimator is negative but not significant, and it does not change in the face of different polynomials and the counterfactuals. This allows us to rule out that changing the degree of the polynomial or including more observations in the sample will influence the impact result. Figure 3 has the graphical results for a 2nd degree polynomial. Although the estimates do not reveal any impact, education spending is higher for counterfactuals in the margin, which is accentuated in the case of the weak control.

<<Insert Figure 3 here>>

Table 6 shows the results for the second dependent variable: public education results via PSU scores. The negative impact of the mining municipalities that are strong controls is maintained, although it increases by approximately 10% in magnitude for the different polynomials. This result allows us to account for the robustness of the results in Table 4. However, the impact when considering weak controls with different polynomials lacks statistical significance.

<<Insert Table 6 here>>

Figure 4 shows the results for a second degree polynomial. In the margin the gap is close to 20%, although it is more pronounced when considering the strong control. Meanwhile, the adjustment for the control PSU scores is maintained above the treatment setting. In the case of the weak control, although there are differences in the margin, these are reduced for the rest of the curve, which finally results in the absence of impact established in Table 6.

<<Insert Figure 4 here>>

In order to defend the robustness of the previous estimates against potential spatial autocorrelation in the dependent variables, we exclude the effect of the municipalities that are spatially close to the treated group and that are part of the counterfactuals. In this regard, the weak controls indirectly receive the mining tax through the redistributive mechanism established in the mining code. The level of income received depends in part on what was collected in the municipality where the mining concession is located. Therefore we form concentric rings with a radius of 50 km from the centroid of the treated units and then estimate the impact by excluding from the controls any municipality that falls within the radius. The same procedure is done at 100 km, 150 km and 200 km. [x]

Table 7 details the results for public education spending for the bias-correction and robust estimators. For the strong counterfactual, although the impact decreases and becomes positive up to 100 km, it has no statistical significance. By increasing the magnitude of the concentric radii the impacts are negative, but they are not statistically significant. When considering the weak counterfactual, the impact becomes significant and negative where the magnitude of the impact is gradually increased. Between 50 and 100 km the impact corresponds to CLP $18 million (US$28 thousand). This nearly doubles (CLP $32 million, US$49 thousand) when considering rings between 150 km and 200 km.

<<Insert Table 7 here>>

For the second dependent variable the results are presented in Table 8 and consider the same procedure as detailed above. The negative and significant impacts are maintained when considering both counterfactuals, although they decrease in magnitude. The strong control goes from approximately 36% at 50 km to 21% in favor of the control at 200 km. In the case of weak control, although the magnitude of the negative impact stays close to 22%, this impact increases to 30% for rings between 150 and 200 km.

<<Insert Table 8 here>>

Finally, in order to test for the robustness of the results, a falsification analysis is presented in Table 9, which considers arbitrary and different cutoff points to the one established for calculating the impact. We consider cutoff points of 1.5% and 3.5% which forces treatments to be established as controls or vice versa. This allows us to rule out a placebo effect in the estimates. As expected, for all cases impact has no statistical significance, which validates the results obtained for the cutoff point established by law and used in the different analyses previously presented.

<<Insert Table 9 here>>

6. Results Discussion and Conclusion

This research evaluates the impact of mining taxes in Chile on indicators of public education, specifically on educational results and the level of investment of municipalities with a high presence of nonrenewable resource extraction. The income from mining patents is aimed at improving the living conditions of the mining municipality and do not impose a tax burden on the local inhabitants. We exploit a set of data corresponding to 345 municipalities over the period of 2010 to 2016 and estimate the impact on two proxies, namely public education spending and the percentage of students that reach the necessary score to access the university system in Chile. To identify the effect, we constructed a treatment group that corresponds to the mining municipalities. We were able to do this by using an exogenous allocation rule and two control groups classified as strong and weak depending on the degree of spatial proximity to the treatments.

We estimate the impact via RDD for a data pool that amounts to 2,102 observations for the period under study. A causal effect (between the mining municipalities and the variables under consideration) is attributed to characteristics in the margin near the cutoff point, where allocation to the groups in comparison approaches an almost random design. In order to verify the robustness of the results we used different methods of RDD in the vicinity of the cutoff point, polynomials to capture the effect of observations far from the cutoff, as well as various Bandwidth methods. We control for spatial autocorrelation by removing municipalities that are at a radii of 50 km, 100 km, 150 km and 200 km from the treatments, from the counterfactuals. Finally, a counterfeit test is calculated in order to corroborate the impact, which induces a placebo effect when using different cutoff points close to 2.5%.

By taking advantage of the exogenous rule of allocation for the groups being compared, the results are robust to potential problems of endogeneity. This is achieved by using observations near the cutoff point, and where the case under study is close to a natural experiment.

The results show an absence of impact for mining municipalities regarding public education spending. This absence of impact is robust against different methods of RDD and established procedures. However, when considering the results graphically, in the margin, mining municipalities invest a smaller amount of resources than the counterfactuals. These municipalities may therefore have a lower level of provision of public education such as teaching staff, infrastructure in educational establishments, and enrollment in public establishments, all of which are factors in lower educational results.

We find that mining municipalities have a negative result in terms of PSU scores ≥450 points, and that it is significant and robust compared to counterfactual ones when using different estimation methods. In particular, this negative impact is between 20% and 37% and increases by 10% when considering polynomials, which is deepened when compared to strong controls. This establishes a scenario that is not conducive to the municipalities that harbor a high volume of mining activity, and consequently, the public policy objective established by law in accordance with the extra income for the benefit of the population would not be met.

These results have important implications for public policies, especially for areas with a high level of exploitation of non-renewable resources. It is likely that the extra income will not be used to improve the education system or local infrastructure, but rather be absorbed by the higher living costs faced by mining towns in Chile. This includes higher wages as well as higher costs for goods and services. Our results in regards to access to higher education are also discouraging and reveal a local education system that is failing to prepare current and future generations of young people to enter the labor market. Despite the extra income, the capacity to boost the local economy of mining municipalities is limited. These results constitute evidence to partly discard the benefits of the public policy instrument and, consequently, the role of the extra income as a compensation for the negative externalities derived from mining.

However, we do recognize the imperfection of the proxies used to measure the impact, derived mainly from the short period of analysis. Therefore, future research must use other indicators that will allow for long-term inference. At the same time, it is necessary to complement and validate the results with other impact assessment techniques and to exploit the communal data panel.

Referencias

Annabi, N., Harvey, S., & Lan, Y. (2011). Public expenditures on education, human capital and growth in Canada: An OLG model analysis. Journal of Policy Modeling, 33(6), 852-865.

Andrews-Speed, P. & Rogers, C. D. (1999). Mining taxation issues for the future. Resources Policy, 25(4):221-227.

Atkinson, G. & Hamilton, K. (2003). Savings, growth and the resource curse hypothesis. World Development, 31(11):1793{1807.

Baldacci, E., Guin-Siu, M. T., & Mello, L. D. (2003). More on the effectiveness of public spending on health care and education: a covariance structure model. Journal of International Development, 15(6): 709-725.

Beraldo, S., Montolio, D., & Turati, G. (2009). Healthy, educated and wealthy: A primer on the impact of public and private welfare expenditures on economic growth. The Journal of Socio- Economics, 38(6): 946-956.

Bjorvatn, K., Farzanegan, M. R., & Schneider, F. (2012). Resource curse and power balance: Evidence from oil-rich countries. World Development, 40(7):1308-1316.

Brollo, F., Nannicini, T., Perotti, R., & Tabellini, G. (2013). The political resource curse. The American Economic Review, 103(5):1759-1796.

Calonico, S., M. D. Cattaneo, M. H. Farrell, and R. Titiunik. 2016a. Regression Discontinuity Designs using Covariates. Working Paper.

Calonico, S., M. D. Cattaneo, M. H. Farrell, and R. Titiunik. 2016b. rdrobust: Software for Regression Discontinuity Designs. Working Paper.

Dahlberg, M., Mörk, E., Rattsø, J., & Ågren, H. (2008). Using a discontinuous grant rule to identify the effect of grants on local taxes and spending. Journal of Public Economics, 92(12), 2320-2335.

Dettman, S. & Pepinsky, T. B. (2016). Resource shocks and local public goods: A tale of two districts. Unpublished Manuscript.

Dobra, J. & Dobra, M. (2013). State mineral production taxes and mining law reform. Resources Policy, 38(2):162-168.

Douangngeune, B., Hayami, Y., & Godo, Y. (2005). Education and natural resources in economic development: Thailand compared with Japan and Korea. Journal of Asian Economics, 16(2), 179-204.

Emerson, C. (1982). Mining enclaves and taxation. World Development, 10(7):561-571.

Ergas, H. & Pincus, J. (2014). Have mining royalties been beneficial to australia? Economic Papers: A journal of applied economics and policy, 33(1):13-28.

Gupta, S., Verhoeven, M., & Tiongson, E. R. 2002. The effectiveness of government spending on education and health care in developing and transition economies. European Journal of Political Economy, 18(4): 717-737.

Gylfason, T. (2001). Natural resources, education, and economic development. European Economic Review, 45, 847-859.

Hong, J. J. T. (2014). How resource endowments affect the provision of public services: Evidence from china. In Political Science Seminar Series, NYU Abu Dhabi, UAE.

Hughes, H. (1975). Economic rents, the distribution of gains from mineral exploitation, and mineral development policy. World Development, 3(11-12):811-825.

Iverson, R. D. & Maguire, C. (2000). The Relationship between Job and Life Satisfaction: Evidence from a Remote Mining Community. *Human Relations, 53(6):*807-839.

Lee, D. S., & Lemieuxa, T. (2010). Regression discontinuity designs in economics. *Journal of economic literature, 48*(2): 281-355.

Loayza, N. & Rigolini, J. (2016). The Local Impact of Mining on Poverty and Inequality: Evidence from the Commodity Boom in Peru. *World Development, 84*(C):219-234.

Mahdavi, P. (2012). The Oil Advantage: Incumbency Effects in Iranian Parliamentary Elections. Michaels, G. (2011). The long term consequences of resource-based specialisation. The Economic Journal, 121(551), 31-57.

Nurkse, R. (1958). Trade fluctuations and buffer policies of low-income countries, Kyklos 11(2): 141–154.

Olsson, O., & Valsecchi, M. (2012). Resource Windfalls and Public Goods: Evidence From a Policy Reform. Economic Studies Department of Economics School Of Business, Economics and Law University of Gothenburg.

Papyrakis, E., & Gerlagh, R. 2004. The resource curse hypothesis and its transmission channels. Journal of Comparative Economics, 32(1): 181-193

Prebisch, R. (1950). The economic development of Latin America and its principal problems. New York: United Nations Press.

Rivera, N. M. & Paredes, D. (2016a). Do resource taxes crowd out other local taxes? Evidence from Chile. Working Paper.

Rivera, N. M & Paredes, D. (2017b). Mineral Taxes and the Local Provision of Public Goods in Mining Communities.

Robinson, J. A., Torvik, R., & Verdier, T. (2006). Political foundations of the resource curse. Journal of development Economics, 79(2):447-468.

Singer, H. W. (1950). The distribution of gains between investing and borrowing countries, The American Economic Review, 40(2): 473–485.

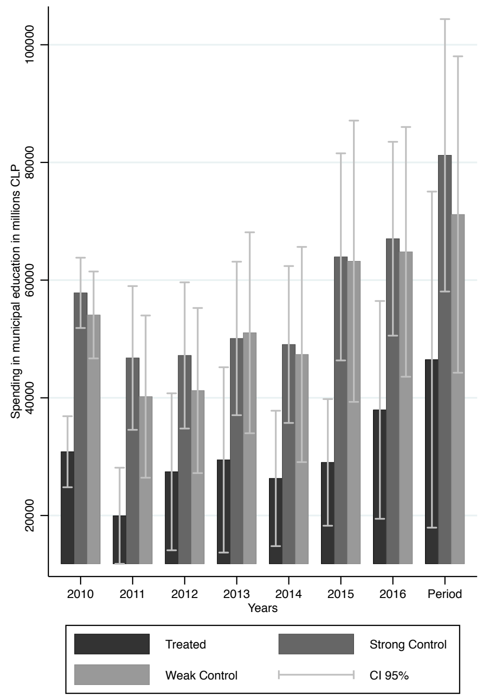
Shao, S., & Yang, L. 2014. Natural resource dependence, human capital accumulation, and economic growth: A combined explanation for the resource curse and the resource blessing. Energy Policy, 74: 632-642.

Stinson, T. F. (1977). State taxation of mineral deposits and production (Vol. 1). Environmental Protection Agency, Office of Research and Development, Office of Energy, Minerals and Industry.

Skovron, C., & Titiunik, R. (2015). A practical guide to regression discontinuity designs in political science. American Journal of Political Science.

Zhuang, Y., & Zhang, G. (2016). Natural resources, rent dependence, and public goods provision in China: evidence from Shanxi's county-level governments, The Journal of Chinese Sociology, 3(1): 3-20.

7. Figures and Tables



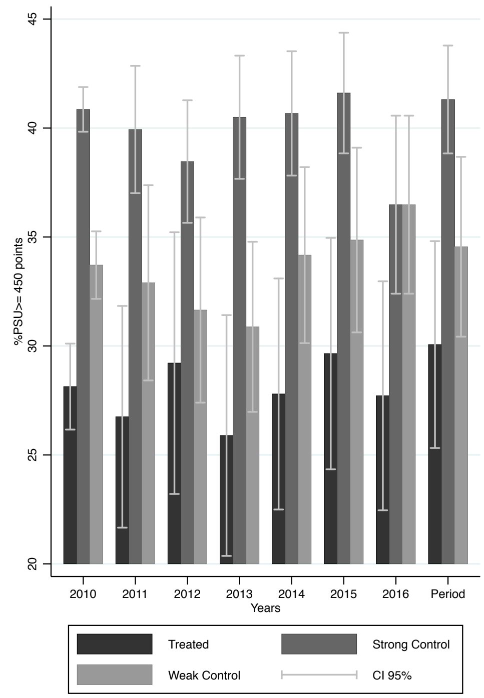


Figure 1. Descriptive statistics dependents variables, 2010-2016
Source: Own elaboration based on SINIM 2017.

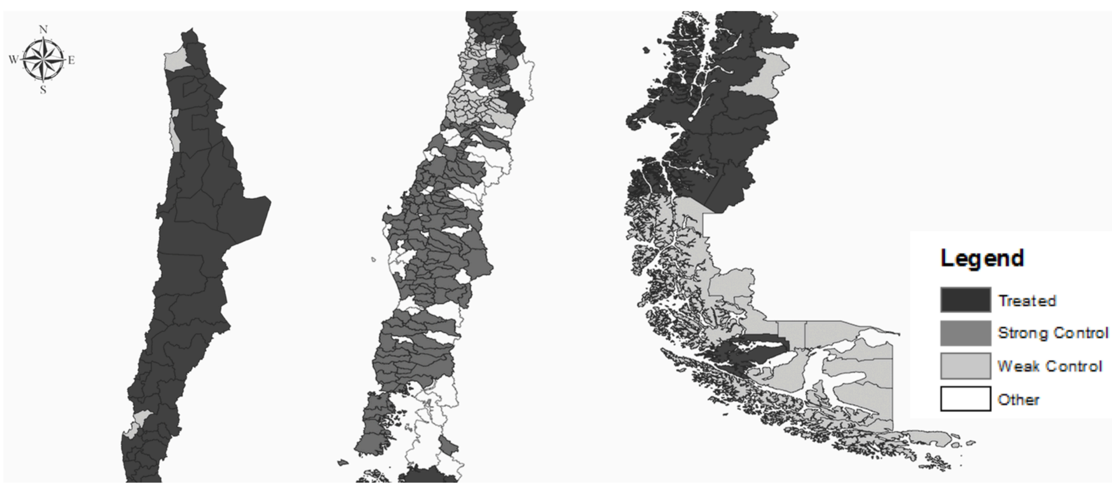


Figure 2. Spatial localization of treated and controls municipalities in 2010
Source: Own elaboration based on SINIM 2017.

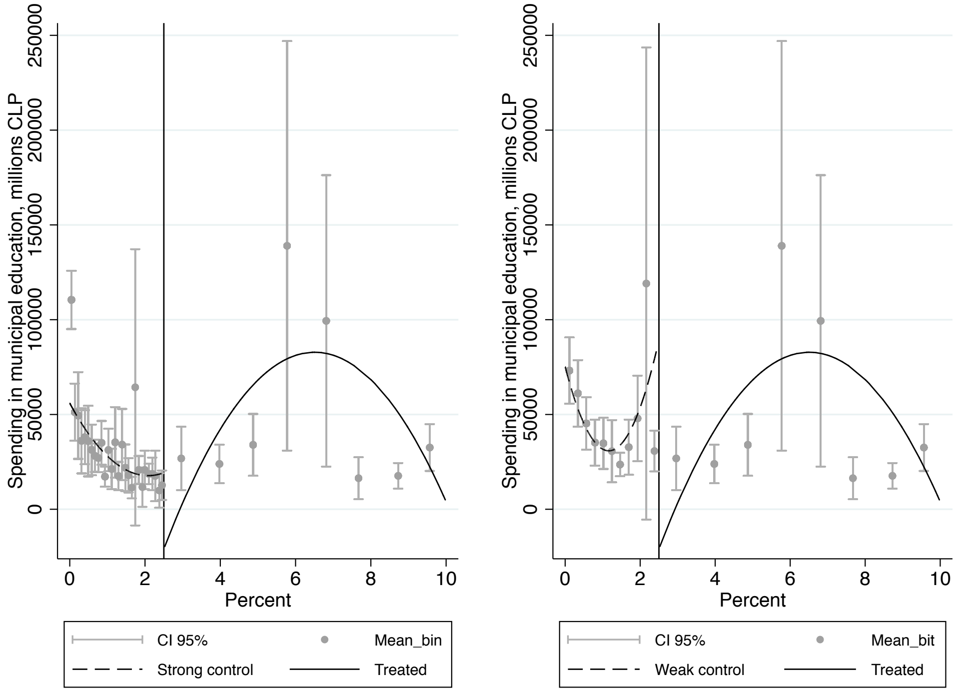


Figure 3. 2nd degree polynomial fit in spending in municipal education, 2010-2016

Source: Own elaboration based on SINIM 2017.

Note: We present only information for 10% in the horizontal axis. The results for higher percent can be obtained from the authors.

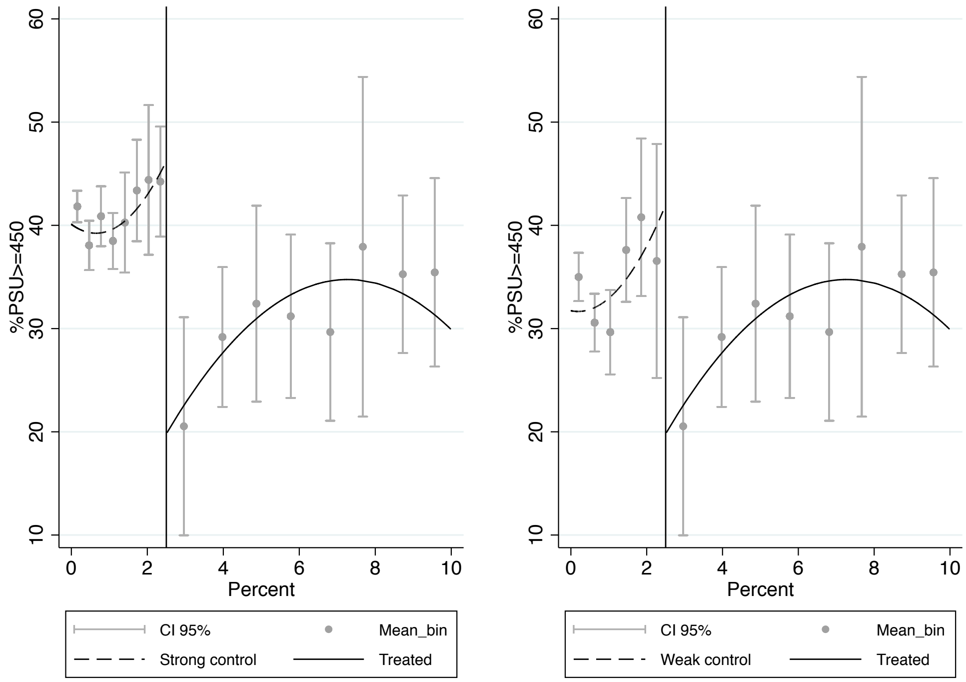


Figure 4. 2nd degree polynomial fit in % PSU $\geq$ 450, 2010-2016

Source: Own elaboration based on SINIM 2017.

Note: We present only information for 10% in the horizontal axis. The results for higher percent can be obtained from the authors.

Table 1. Treated and control municipalities, 2010-2016

Detail	Non-mining municipalities $c < 2.5\%$	Mining municipalities $c \geq 2.5\%$	Total
Non-mining region	Strong control	Non-analysed	
2010	128	35	163
2011	130	40	170
2012	135	37	172
2013	139	35	174
2014	143	33	176
2015	149	23	172
2016	183	22	205
Total	1,007	225	1,232
Mining region	Weak control	Treated	
2010	66	59	125
2011	62	59	121
2012	62	59	121
2013	65	59	124
2014	68	57	125
2015	67	56	123
2016	75	56	131
Total	465	405	870
Total	1,472	630	2,102

Source: Own elaboration based on SINIM 2017.

Note: c corresponds to the cutoff point attributed to the institutional design that denotes mining municipalities.

Table 2. Descriptive statistics of dependent variables, 2010-2016

Variables	Treated		Strong control		Weak control	
	Mean	CI (95%)	Mean	CI (95%)	Mean	CI (95%)
Spending in municipal education	30,836	[24,798, 36,874]	57,837	[51,867, 63,807]	54,080	[46,693, 61,467]
Obs	401		1,006		464	
% PSU≥ 450	28.135	[26.163, 30.107]	40.856	[39.830, 41.883]	33.710	[32.159, 35.261]
Obs	405		1,007		465	

Source: Own elaboration based on SINIM 2017.

Note: spending in municipal education in millions CLP. The discrepancy between number of observations of both variables responds to the information restrictions of some municipalities that do not report information of the spending in municipal education.

Table 3. Descriptive statistics of the independent variables, 2010-2016

Variables	Treated		Strong control		Weak control	
	Mean	CI (95%)	Mean	CI (95%)	Mean	CI (95%)
% of mining patents in IPP	27.956	[25.852, 30.061]	0.508	[0.472, 0.545]	0.615	[0.563, 0.666]
Municipal Population	26,908	[26,908, 32,491]	67,427	[60,867, 73,987]	52,333	[45,681, 58,984]
Own income (IP)	3,733	[588, 49,792]	7,236	[720, 128,860]	6,357	[498, 72,610]
% of teachers per student	16.960	[0, 32.810]	18.803	[9.360, 47.360]	17.716	[4.500, 29.750]
Average monthly enrollment	3,523	[0, 46,584]	5,278	[457, 35,142]	4,395	[9, 26,755]
Number of public schools *	13,825	[0, 101]	19,557	[2, 567]	13,869	[1, 56]
Poverty index	14.422	[13.692, 15.149]	20.170	[19.619, 20.722]	13.790	[13.283, 14.298]
Obs	405		1,007		465	

Source: Own elaboration based on SINIM 2017.

Note: IP in millions CLP * There are municipalities in which the number of schools is not reported, 16 treated, 23 strong controls and 16 weak controls.

Table 4. RDD effect of mining municipalities in dependent variables with a 1st degree polynomial, 2010-2016

Variable/Group/ RDD method	Coef	P-v	CI (95%)	Coef	P-v	CI (95%)
Spending in municipal education				% PSU ≥450		
Strong control				**Strong control**		
Conventional	-10,754	0.661	[-58,853.1, 37,345.3]	-37.603	0.000	[-51.225, -23.981]
Bias-corrected	-10,541	0.668	[-58,640.5, 37,557.8]	-36.302	0.000	[-49.925, -22.680]
Robust	-10,541	0.669	[-58,913.0, 37,830.3]	-36.302	0.000	[-50.810, -21.795]
Bandwidth/MSE*	(0.474; 1.016)			(0.610; 1.722)		
Obs.Eff*	(33; 9)			(42; 22)		
Weak control				**Weak control**		
Conventional	25,174	0.128	[-72,67.6, 57,616.2]	-13.012	0.012	[-23.185, -2.840]
Bias-corrected	-18,289	0.269	[-50,730.5, 14,153.3]	-21.497	0.000	[-31.669, -11.325]
Robust	-18,289	0.329	[-55,025.0, 18,447.7]	-21.497	0.001	[-34.583, -8.411]
Bandwidth/MSE*	(4.002; 14.303)			(5.068; 12.692)		
Obs.Eff*	(448; 148)			(449; 138)		

Source: Own elaboration based on SINIM 2017.
Note: We present three estimators of RDD: conventional, bias-corrected and robust. Bandwidth method: msetwo, (*Left of c; Right of c). Controls: % of mining patents in IPP, municipal Population, own income (IP), % of teachers per student, average monthly enrollment, number of public schools, poverty index and yearly dummies.

Table 5. RDD robust effect of mining municipalities in spending in municipal education with 2, 3 and 4 degree polynomial, 2010-2016

Group/ Degree polynomial	Coef	P-v	CI (95%)	Obs.Eff.*	BW loc. poly/MSE*
Strong control					
2	-4,085.621	0.852	[-47,069.863, 38,898.62]	(33; 44)	(0.442; 2.605)
3	-14,290.649	0.476	[-53,566.201, 24,984.904]	(42; 129)	(0.600; 11.022)
4	-11,154.497	0.642	[-58,121.524, 35,812.530]	(58; 112)	(0.740; 8.500)
Weak control					
2	-31,528.182	0.112	[-70,430.250, 7,373.887]	(448; 146)	(4.461; 13.988)
3	-26,867.587	0.292	[-76,838.891, 23,103.717]	(448; 177)	(4.918; 18.724)
4	12,722.196	0.694	[-50,576.315, 76,020.709]	(448; 219)	(5.058; 24.133)

Source: Own elaboration based on SINIM 2017.
Note: Bandwidth method: msetwo, (*Left of c; Right of c). The results for the other RDD methods can be obtained from the authors. Controls: % of mining patents in IPP, municipal Population, own income (IP), % of teachers per student, average monthly enrollment, number of public schools, poverty index and yearly dummies.

Table 6. RDD robust effect of mining municipalities in % PSU≥ 450 with 2, 3 and 4 degree polynomial, 2010-2016

Group/ Degree polynomial	Coef	P-v	CI (95%)	Obs.Eff.*	BW loc. poly/MSE*
Strong control					
2	-42.356	0.000	[-63.332, -21.380]	(42; 43)	(0.612; 2.576)
3	-42.010	0.000	[-64.568, -19.452]	(43; 84)	(0.653; 6.095)
4	-41.610	0.001	[-66.009, -17.212]	(61; 122)	(0.799; 9.913)
Weak control					
2	-10.245	0.143	[-23.955, 3.466]	(449; 142)	(4.742; 13.590)
3	0.940	0.895	[-13.061, 14.941]	(449; 217)	(5.016; 22.993)
4	-1.542	0.867	[-19.637, 16.551]	(449; 191)	(5.546; 19.841)

Source: Own elaboration based on SINIM 2017.
Note: Bandwidth method: msetwo, (*Left of c; Right of c). The results for the other RDD methods can be obtained from the authors. Controls: % of mining patents in IPP, municipal Population, own income (IP), % of teachers per student, average monthly enrollment, number of public schools, poverty index and yearly dummies.

Table 7. RDD effect of mining municipalities in spending in municipal education per km, 2010-2016

Variable/Group/ RDD Methods	Coef	P-v	CI (95%)	Coef	P-v	CI (95%)
Strong control				**Weak control**		
50 km						
Bias-corrected	6,081.2	0.662	[-21,168.7, 33,331.1]	-17,059.0	0.320	[-50,708.4, 16,590.1]
Robust	6,081.2	0.678	[-22,637.2, 34,799.7]	-17,059.0	0.319	[-50,606.6, 16,488.2]
Bandwidth/MSE*	(0.842; 3.186)			(6.560; 22.735)		
Obs.Eff.*	(60; 55)			(283; 212)		
100 km						
Bias-corrected	2,645.5	0.843	[-23,562.6, 28,853.6]	-18,928.0	0.045	[-37,471.0, **-385.9**]
Robust	2,645.5	0.856	[-25,971.6, 31,262.6]	-18,928.0	0.120	[-42,785.8, 4,928.9]
Bandwidth/MSE*	(2.392; 4.899)			(10.116; 25.362)		
Obs.Eff.*	(548; 78)			(113; 227)		
150 km						
Bias-corrected	-2,064.4	0.877	[-28,147.1, 24,018.2]	-33,844.0	0.001	[-54,273.6, -13,413.5]
Robust	-2,064.4	0.887	[-30,477.5, 26,348.7]	-33,844.0	0.007	[-58,528.6, -9,158.4]
Bandwidth/MSE*	(2.539; 5.283)			(9.672; 24.961)		
Obs.Eff.*	(757; 80)			(56; 222)		
200 km						
Bias-corrected	-5,008.6	0.712	[-31,594.1, 21,576.8]	-32,140.0	0.002	[-52,203.4, -12,077.1]
Robust	-5,008.6	0.733	[-33,822.4, 23,805.2]	-32,140.0	0.010	[-56,568.2, -7,712.3]
Bandwidth/MSE*	(2.752; 5.609)			(9.623; 24.974)		
Obs.Eff.*	(713; 83)			(51; 222)		

Source: Own elaboration based on SINIM 2017.
Note: Bandwidth method: msetwo, (*Left of c; Right of c). The results for the other RDD methods can be obtained from the authors. Controls: % of mining patents in IPP, municipal Population, own income (IP), % of teachers per student, average monthly enrollment, number of public schools, poverty index and yearly dummies.

Table 8. RDD effect of mining municipalities in $\% \ PSU \geq 450$ per km, 2010-2016

Variable/Group/ RDD Methods	Coef	P-v	CI (95%)	Coef	P-v	CI (95%)
Strong control				**Weak control**		
			50 km			
Bias-corrected	-35.726	0.000	[-49.046, -19.983]	-22.067	0.000	[-33.154, -11.391]
Robust	-35.726	0.000	[-49.774, -19.256]	-22.067	0.001	[-35.913, -8.632]
Bandwidth/MSE*		(0.577; 2.012)			(6.861; 14.055)	
Obs.Eff.*		(40; 30)			(284; 146)	
			100 km			
Bias-corrected	-21.300	0.000	[-31.895, -7.724]	-22.697	0.002	[-37.054, -8.339]
Robust	-21.300	0.000	[-29.921, -6.430]	-22.697	0.026	[-42.737, -2.657]
Bandwidth/MSE*		(2.410; 7.774)			(9.307; 14.684)	
Obs.Eff.*		(573; 108)			(114; 150)	
			150 km			
Bias-corrected	-20.843	0.000	[-27.155, -7.171]	-31.104	0.002	[-52.870, -11.552]
Robust	-20.843	0.000	[-28.478, -5.849]	-31.104	0.019	[-58.643, -5.779]
Bandwidth/MSE*		(2.767; 8.468)			(8.685; 14.677)	
Obs.Eff.*		(757; 112)			(57; 150)	
			200 km			
Bias-corrected	-21.477	0.000	[-27.373, -7.535]	-28.980	0.005	[-51.398, -9.912]
Robust	-21.477	0.000	[-28.827, -6.080]	-28.980	0.038	[-58.392, -2.918]
Bandwidth/MSE*		(3.166; 9.588)			(8.492; 14.679)	
Obs.Eff.*		(713; 119)			(52; 150)	

Source: Own elaboration based on SINIM 2017.
Note: Bandwidth method: msetwo, (*Left of c; Right of c). The results for the other RDD methods can be obtained from the authors. Controls: % of mining patents in IPP, municipal Population, own income (IP), % of teachers per student, average monthly enrollment, number of public schools, poverty index and yearly dummies.

Table 9. Results for Placebo cutoffs RDD Test.

Placebo Cutoff	Coef	P-v	CI (95%)	Obs.Eff. (Left of c; Right of c)	Bandwidth/MSE (Left of c; Right of c
Spending in municipal education					
Strong control					
1.5	-1,273.7	0.814	[-9,273.4, 9,820.4]	(254; 146)	(0.938; 5.300)
3.5	13,370.0	0.482	[-22,368.0, 42,008.0]	(8; 91)	(0.722; 6.309)
Weak control					
1.5	11,558.0	0.486	[-20,937.8, 44,053.1]	(406; 226)	(5.996; 14.922)
3.5	-32,321.0	0.128	[-73,983.3, 9,341.2]	(457; 220)	(3.790; 24.565)
$\% \text{ PSU} \geq 450$					
Strong control					
1.5	5.191	0.248	[-3.620, 14.002]	(391; 145)	(1.194; 5.277)
3.5	-3.115	0.512	[-12.427, 6.197]	(6; 98)	(0,563; 6,662)
Weak control					
1.5	-2.232	0.628	[-11.268, 6.803]	(405; 206)	(5.250; 17.574)
3.5	-3.112	0.587	[-14.343, 8.120]	(458; 147)	(5.128; 14.774)

Source: Own elaboration based on SINIM 2017.

Note: Bandwidth method: msetwo, (*Left of c; Right of c). Robust estimator. The results for the other RDD methods can be obtained from the authors. Controls: % of mining patents in IPP, municipal Population, own income (IP), % of teachers per student, average monthly enrollment, number of public schools, poverty index and yearly dummies.

[i] The PSU is a standardized test with multiple choice questions for students who wish to access the Chilean university system. It is elaborated in Chile by the Department of Evaluation, Measurement and Educational Registration (DEMRE).

[ii] Administratively, Chile is divided into 15 regions, 54 provinces and 345 *comunas* or municipalities. In political-administrative terms, regions and municipalities are considered. A mining municipality must be located in a mining region. A mining region is one in which mining activity contributes to at least 2.5% of the regional GDP according to the second paragraph of the first transitional article of the Supreme Decree No. 746 from the Ministry of Finance in 2011. For more information see: Bulletin No. 8272-08. Available here: http://www.senado.cl/appsenado/index.php?mo=sesionessala&ac=getCuenta&iddocto=34914# (May, 2012).

[iii] The strong group is located in non-mining regions and therefore does not receive income from mining taxes. Meanwhile, the weak group receives the tax directly, as set up by the government. *Ingresos Propios Permanentes* (IPP) or the Municipal Permanent Income is equivalent to the total municipal revenue and corresponds to the income generated by the municipality via municipal management, which is why it is considered an important indicator for the capacity for self-financing. For more information visit: http://www.dipres.gob.cl/572/articles-114713_doc_pdf.pdf.

[iv] The figures consider the sum of all municipal data over the entire period. The variability (during the period under analysis) in the mining municipalities must be taken into consideration via the contribution of the mining patents over the IPP. 225 communes are left out of the analysis because, even though their mining patent contribution/IPP rate is greater than 2.5%, they are not located in a mining region.

[v] The effect of a mining municipality on its non-mining municipality (but belongs to a mining region) neighbors is excluded.

[vi] http://datos.sinim.gov.cl

[vii] Given the low variability in treatment and controls, we consider working with the totals for the period.

[viii] The group is to the right of the cutoff point. However, it does not meet the criteria necessary to be classified as a treatment or control. This is because the municipalities are not in mining regions, and because they must be located to the left of the cutoff point in order to be a control.

[ix] Corresponds to the *Ingresos Propios Permanentes* (IPP) or the Municipal Permanent Income plus any transfer from the *Fondo Común Municipal* (FCM) or the Municipal Common Fund.

[x] The minimum distance between treatments and weak counterfactuals is approximately 30 km.