GĚRENS | ESCUELA DE POSTGRADO

Septiembre de 2020

Documento de Trabajo Nº 001-2020-DI

Working Paper Nº 001-2020-DI. ISSN: 2664-0120

Country Competitiveness and Investment Allocation in the Mining Industry: A survey of the literature and new empirical evidence

Autores

Arturo Vásquez Cordano
Rodrigo Prialé Zevallos

Escuela de Postgrado GĚRENS
Dirección de Investigación

Country Competitiveness and Investment Allocation in the Mining Industry: A survey of the literature and new empirical evidence

Documento de Trabajo N° 001-2020-DI. ISSN: 2664-0120

Autores: Arturo Vásquez Cordano, Ph.D. ©
Rodrigo Prialé Zevallos, Ph.D. ©

Primera versión: Septiembre del 2020.

Citar el documento como: Vásquez Cordano, Arturo y Rodrigo, Prialé Zevallos (2019). *Country Competitiveness and Investment Allocation in the Mining Industry: A survey of the literature and new empirical evidence.* Documento de Trabajo N° 001-2020-DI. Dirección de Investigación – Escuela de Postgrado GĚRENS, Perú.

Se solicita indicar en lugar visible la autoría y la fuente de la información. Para comentarios o sugerencias dirigirse a:

Escuela de Postgrado GĚRENS
Avenida Primavera N° 1050, 3er piso, Chacarilla del Estanque, Santiago de Surco. Lima, Perú.

Teléfono: (01) 702 9800 – Anexo: 148/149
Portal corporativo: www.gerens.pe
Correo electrónico: investigacion@gerens.pe

Country Competitiveness and Investment Allocation in the Mining Industry: A survey of the literature and new empirical evidence

Arturo L. Vásquez Cordano[1 3]
GĚRENS Graduate School

Rodrigo Prialé Zevallos[2 3]
GĚRENS Graduate School

Abstract

Mining exploration investment is the primary driver of future mining production. Without exploration investment, it is not possible to sustain metals production. Countries with higher mining competitiveness will tend to attract more massive amounts of exploration investments. According to the so-called "traditional" view, the geological potential of a country is a crucial determinant of its mining competitiveness. This proposition implies that the geological potential would be the main driver for the allocation of exploration investments around the world. In more recent years, an "alternative" view of mining competitiveness emerged. According to this hypothesis, the investment climate of a country is the primary determinant of its mining competitiveness. However, the empirical evidence supporting the validity of this "alternative" view is still scarce.

The goal of this article is to analyze, theoretically and empirically, the validity of these two competing views. First, we survey the literature on the subject to identify the main determinants of mining exploration expenditures, which is the leading indicator of mining competitiveness identified in the literature. Second, to analyze the determinants of the mining exploration expenditures considering their features, we develop an exponential mean model to test the validity of the "alternative" view. We use the Poisson Pseudo-Maximum Likelihood (PPML) method to obtain the parameter estimates given the non-linear and skewed nature of our dependent variable.

Working with a cross-sectional dataset of 72 countries for the year 2014, we find strong empirical support for the "alternative" view of mining competitiveness. Total budgeted mining exploration expenditures are determined not only by the geological potential of countries, as the standard theory of international trade argues, but also by the investment climate. Besides,

[1] Corresponding author: Avenida Primavera 1050, 3rd floor, Santiago de Surco, Lima, Peru. Email: avasquez@gerens.pe. Arturo L. Vásquez Cordano is Director of Research and Associate Professor of Economics and Business at GĚRENS Graduate School. He is also Assistant Professor of Economics at the Pontifical Catholic University of Peru.

[2] Rodrigo Prialé Zevallos is Chief Executive Officer and Professor of Economics and Business at GĚRENS Graduate School, Lima, Peru. Email: rpriale@gerens.pe

[3] We thank Orlando Anaya, Paola Rojas, and Elibeth Cirilo for their valuable research assistance. We also thank GĚRENS Graduate School for its financial support to develop this article under Research Grant N° 001-2017-DI/EPG.

we analyze the impact on mining competitiveness of two additional variables: social conflicts and population density. Our results show that these two variables are also statistically significant determinants of mining competitiveness among countries. Likewise, regional elasticities are estimated to measure the impact of the control variables on the mining competitiveness of countries located in different regions. Countries included in the sample are grouped into six regions: North America, Oceania, Europe, Latin America, Asia, and Africa. Through a quintile analysis, we find that the investment climate has an elastic impact on the attraction of mining exploration investments, but only in the first five deciles of the distribution. At the same time, the geological potential begins to have a relevant but still inelastic impact starting in the sixth decile. These findings can help policymakers and businesspeople to develop strategic plans to attract mining investments and promote economic growth in different jurisdictions.

JEL Classification: C21 (Econometric Cross-Sectional Models), C52 (Model Evaluation, Validation, and Selection), F14 (Empirical Studies of Trade), F21 (International Investment), L72 (Mining, Extraction, and Refining: Other Nonrenewable Resources), Q72 (Issues in International Trade), Q38 (Government Policy).

Keywords: mining competitiveness, mining exploration investment allocation, social conflicts, Poisson Pseudo-Maximum Likelihood method, investment climate, geological potential, regional elasticities.

Competitividad Nacional y la Asignación de Inversiones en la Industria Minera: Revisión de la Literatura y Nueva Evidencia Empírica

Arturo L. Vásquez Cordano[4]
Escuela de Postgrado GĚRENS

Rodrigo Prialé Zevallos[5] [6]
Escuela de Postgrado GĚRENS

La inversión en exploración minera es el principal impulsor de la producción minera a futuro. Sin inversión en exploración, no es posible sostener la producción de metales a largo plazo. Los países con mayor competitividad minera tenderán a atraer cantidades mayores de inversiones en exploración. Según el enfoque "tradicional" de la competitividad minera, el potencial geológico de un país es un determinante crucial de su competitividad. Esta proposición implica que el potencial geológico sería el principal impulsor de la asignación de inversiones en exploración en todo el mundo. En los últimos años, ha surgido una visión "alternativa" de la competitividad minera. Según esta hipótesis, el clima de inversión de un país es el principal determinante de su competitividad. Sin embargo, las pruebas empíricas que respaldan la validez de esta visión "alternativa" siguen siendo escasas.

El objetivo de este artículo es analizar, teórica y empíricamente, la validez de estos dos puntos de vista. En primer lugar, se hace un estudio de la bibliografía sobre el tema para identificar los principales determinantes de los gastos en exploración minera, que es el principal indicador de la competitividad minera identificado en la literatura. En segundo lugar, para analizar los determinantes de los gastos de exploración minera, desarrollamos un modelo de media exponencial de Poisson (PPML) para comprobar la validez de la visión "alternativa". Utilizamos el método de Pseudo Máxima Verosimilitud para obtener las estimaciones de los parámetros, dada la naturaleza no lineal y sesgada de nuestra variable dependiente.

Trabajando con un conjunto de datos de corte transversal de 72 países para el año 2014, encontramos evidencia empírica robusta a favor de la visión "alternativa" de la competitividad minera. Los gastos totales presupuestados de exploración minera están determinados no sólo por el potencial geológico de los países, como sostiene la teoría estándar del comercio

[4] Arturo L. Vásquez Cordano es Director de Investigación y Profesor Asociado de Economía y Finanzas en la Escuela de Postgrado GĚRENS. Asimismo, es Profesor Auxiliar de Economía de la Pontificia Universidad Católica del Perú. Email: avasquez@gerens.pe.

[5] Rodrigo Prialé es Gerente General y Profesor Principal de Economía y Finanzas en la Escuela de Posgrado GĚRENS. Email: rpriale@gerens.pe

[6] Agradecemos a Orlando Anaya, Paola Rojas y Elibeth Cirilo por su valiosa asistencia de investigación durante la realización de este estudio. Agradecemos también a la Escuela de Postgrado GĚRENS por asistencia financiera durante el desarrollo de este artículo a través del Proyecto de Investigación Nº 001-2017-DI/EPG.

internacional, sino también por el clima de inversiones. Además, se analiza el impacto en la competitividad minera de dos variables adicionales: los conflictos sociales y la densidad de población. Nuestros resultados muestran que estas dos variables son también determinantes estadísticamente significativos de la competitividad minera entre los países.

Asimismo, se estiman las elasticidades regionales para medir el impacto de las variables de control en la competitividad minera de los países ubicados en diferentes regiones. Los países incluidos en la muestra se agrupan en seis regiones: América del Norte, Oceanía, Europa, América Latina, Asia y África. Mediante un análisis de quintiles, se observa que el clima de inversión tiene un impacto elástico en la atracción de las inversiones en exploración minera, pero sólo en los cinco primeros deciles de la distribución. Al mismo tiempo, el potencial geológico comienza a tener un impacto relevante pero aún inelástico a partir del sexto decil. Estas conclusiones pueden ayudar a los hacedores de política minera y a los empresarios a elaborar planes estratégicos para atraer inversiones mineras y promover el crecimiento económico en diferentes jurisdicciones.

Clasificación JEL: C21, C52, F14, F21, L72, Q72, Q38.

Palabras clave: competitividad minera, asignación de inversiones en exploración minera, conflictos sociales, modelo de Poisson de pseudo máxima verosimilitud, clima de inversiones, potencial geológico, elasticidades regionales.

List of Figures

List of Tables

1. Introduction

In recent years, several articles in the minerals economics literature have studied the countries' competitiveness for attracting foreign direct investment (FDI) to finance mining exploration activities. Exploration investment expenditures in the mining sector is a crucial driver to discover or increase mineral reserves and sustain mining operations worldwide.

The "traditional view of mining competitiveness," based on standard international trade theory, points out that the *geological potential* (mineral endowment) explains why certain countries have a competitive advantage to produce some mineral products and why these countries attract FDI to sustain exploration activities. In contrast, the "alternative view of mining competitiveness," initially proposed by Tilton (1983, 1992) and Johnson (1990), argues that not only geological resources explain the competitiveness of a country to attract mining investments, but also the *climate* to do business is an essential source of this competitiveness. In turn, the investment climate depends on political stability, tax rules, the quality of institutions, among other factors. In the "alternative view" of mining competitiveness, the investment climate of a country is a critical determinant of the allocation of mining exploration expenditures among different jurisdictions.

This paper aims to review the debate about the factors that explain the allocation of mining exploration investment across countries, and provides new empirical evidence supporting the alternative view of mining competitiveness. We organize the study as follows. First, we review the literature on the subject, going from the original ideas regarding the mining competitiveness of a country to the analysis of the empirical works developed during the last years, which have provided new insights regarding the validity of the traditional view and the alternative view of the mining competitiveness. There have been efforts to test the validity of the alternative view of mining exploration investment. However, we show that it is possible to improve the econometric analysis to test the hypothesis more adequately, considering the structure and nature of the data available and the functional forms of the models used.

Second, given the "state of the art" regarding this issue, we propose a new analytical framework to understand the relationship among budgeted mining exploration expenditures, geological potential, and countries' investment climate, incorporating in the analysis the effects of social conflicts and population density. Social conflicts around mining investments in host countries have received considerable attention in the literature because they have often affected the operations of mines adversely. Mines might stop operations if the communities do not grant the "social license to operate," destroying value for mining companies' shareholders and diminishing the attractiveness to invest in socially unstable countries. Besides, population density is an essential factor to consider since countries with large populations and small territories have less area available to perform mining explorations and eventually to develop extractive operations, which ends up reducing the countries' capacity to attract exploration investments.

Third, based on the information reported by Estrella, Miranda, and Sánchez (2015), Franasovic (2017), and SNL (2014), we construct a cross-sectional dataset for the year 2014. This dataset contains the critical variables for our analysis: budgeted exploration expenditures of mining firms, geological potential measured by the gross value of mining production, the investment climate index, as well as the number of social conflicts per km^2 and the population density.

After performing a rigorous statistical analysis to evaluate different functional forms that capture the structure of the data, we find that the semi-logarithmic regression model is the specification that fits the data better. This model is equivalent to the Poisson regression, which has good statistical properties according to the literature. Hence, this will be the model used in this article. We then perform the hypothesis test for the alternative view of mining competitiveness, based on the determination of the average elasticity of exploration expenditures concerning our indicators of geological potential and investment climate for the whole sample, and also for the different sub-samples representing regions around the world.

Finally, given the nonlinear relationship that there exists among our variables, we analyze if the effects of both the geological potential and the investment climate indicators are statistically the same over different quintiles of the distribution of the budgeted mining exploration expenditures. This analysis will allow us to find if there is an asymmetric effect of both explanatory variables on the number of exploration expenditures allocated in each group of countries. We draw our conclusions at the end of the article.

2. Background and literature survey

2.1. Theoretical concepts

In recent decades, the mining industry has changed dramatically from a sector mainly controlled by state-owned companies in the 1960s and 1970s to an industry dominated by private companies after the privatization of several state-controlled firms in the 1980s. Today, private international mining companies, including several multinational corporations, are mainly in charge of exploring and developing new mineral deposits and operating existing mines. In this context, the governments of producing countries need to deploy public policies to incentivize private mining companies to allocate capital to their jurisdictions. In that way, they can be successful in the competition for foreign private capital to fund the development of their mineral resources.

The standard international trade literature argues that *factor endowments*, e.g., mineral reserves or the potential to produce large quantities of mining products, can create comparative advantages to attract more capital to the domestic mining industry (Ohlin 1933[7], Moroney 1975,

[7] The factor endowment theory of international trade, or HO theory, was proposed by Swedish economists Eli Hechscher and Bertil Ohlin at the start of the 20th century. In their theory immobile and inelastically supplied factor endowments, such as mineral resources, constitute a source of comparative advantage that induces flow of products between regions and countries. Vanek (1963) version of the theory (HOV theory) establishes that the HO theory in fact predicts flows of factor services. In this regard, mining products are simply the means how these factor services flow across regions. According to Davis and Vásquez Cordano (2013), the HOV theory puts forward, by means of the Rybczynksi Theorem, that an increase in the resource endowment will generate either the start of production and export of the mining product (e.g., copper, gold) that employs the mineral resource (which provides the vehicle for exporting the mineral resource service flow) through new mines, or an increase in the production and export of that mining product in existing mines. Similarly, a reduction of the resource endowment, because of mineral depletion or "resource sterilization" due to stringent policies, can diminish the output and export of the mining product (Tilton 1983, 1992).

Haberler 1977[8], Tilton 1983, Leamer 1984). Under this "traditional view" of mining competitiveness, those countries where it is possible to find valuable mineral deposits will likely attract, *ceteris paribus*, more private capital to their mining sectors. However, given that mineral endowments are the result of geological processes occurred millions of years ago, a country can do little to change the perception of its geological potential. The only policy governments can implement in that regard is providing information to the market about the quantity and quality of a country's geological resources (for example, via the work of its geological survey institutions), so those private companies can use this information for their *in-situ* explorations. The occurrence of discoveries of mineral deposits or a significant level of mineral production in a country can also alter the perceptions about the geological potential in a jurisdiction (Jara, Lagos and Tilton 2008; Tilton and Guzman 2016). In other words, according to the factor endowment trade theory, in an ideal scenario, mining investment should flow to countries that have the most abundant and highest-quality deposits.

Even though the geological potential is always a factor looked over by CEOs, geologists, and investors, several other variables must be considered when deciding where to allocate exploration expenditures. Recent evidence regarding this fact is provided by Tilton and Guzman (2016, Ch. 6) for the case of copper. These authors have shown that there is a statistically significant relationship between copper reserves (as a proxy of mineral endowment) and the production of copper, which suggests that an essential part of the inter-country variation of copper production is related to differences in mineral endowments.[9] However, not all the variation of copper production is related to the reserves, which means that the factor endowment theory provides at most an incomplete explanation of mineral trade and competitiveness. This result explains why in the 1990s, several mining executives and academic researchers argued that there should be other factors besides the geological potential that accounts for a country's attractiveness for mining investments.

This argument is relevant, given the particular characteristics of mining investments.[10] Before making an investment decision, mining companies should be confident that they will recover their investment since once they commit capital to a project, it will become a sunk cost (Barham & Coomes, 2005). According to Dixit and Pindyck (1994: 3,8), sunk costs refer to a type of investments that, once undertaken, cannot be fully recovered through their sale or transfer to other tasks because of their industry-specific characteristics. For instance, the activities of exploring for new mineral deposits, extracting ore, processing minerals, refining, and transporting large quantities of mineral products demand secure facilities with high installation costs.

[8] In the words of Haberler (1977: 4): "The most obvious factors that explain a good deal of international trade are natural resources – land of different quality (including climatic conditions), mineral deposits, etc. No sophisticated theory is required to explain why Kuwait exports oil, Bolivia tin, Brazil coffee and Portugal wine. Because of the deceptive obviousness of many of these cases, economists have spent comparatively little time to study the natural resource trade".

[9] Tilton and Guzman estimate linear regression models where copper production is regressed on reserves lagged 10 years for the periods 1950-1960, 1975-1985 and 2000-2010, finding a positive relationship between both variables. The regressions exhibit R^2 statistics greater than 80%.

[10] The mining industry has certain features that are not found in other industries. These attributes are: a) high capital intensity, b) low labor intensity, c) long lead times, d) high investment risk, e) the exploitation of non-renewable resources, f) finite life of mine, g) volatile mineral markets, h) high operational and environmental risks, i) social conflicts, and j) late payback (Vivoda 2017: 20).

Likewise, the amount of investment in a mine can be significant to achieve a minimum efficient scale of operations. Besides, since mine operations can be in place for years or decades, mining capital investments are usually immobile for a considerable period; therefore, these investments are subject to *high levels of risk* (Naito, Otto, and Eggert 1998; Vivoda 2017). Therefore, if a country wants to be more attractive for mining FDI, it should try to reduce the level of risk that its mining projects face.

In this context, the literature about the "alternative view" of mining competitiveness flourished, introducing in the analysis the investment climate to do business as a new variable to reduce the level of risk of the investments and to attract capital to the domestic mining industry (Tilton 1983, Johnson 1990, Eggert 1992, Otto 1992, Tilton 1992, Vivoda 2017). Governments have several policy alternatives to shape the investment climate in their countries. They have at their disposal the capability to change their mineral taxation and to design the institutional organization and governance of the public agencies in charge of the regulation of the mining industry and complementary sectors. Likewise, governments can use public expenditure to improve the quality of public infrastructure (roads, ports, transmission lines, power generators, telecommunication networks), as well as to promote stable financial sectors, the transparency of labor markets, among other measures.[11]

Under this view, public policies oriented to improve the investment climate can create favorable conditions for mining companies. In economic terms, these conditions should help to reduce the production costs to mine an additional unit of reserve in a country, so mining operations in the country can exhibit cheap marginal costs to face international competition. In this sense, a country with low marginal costs of extraction, *ceteris paribus*, is more attractive for the allocation of mining companies' scarce exploration capital (Tilton 1992).

In the next section, we review the empirical literature that has analyzed the validity of the traditional and alternative view of mining competitiveness in recent years. We aim to provide a critical analysis of the empirical studies related to the factors that explain the allocation of exploration mining investment expenditures, highlighting the advantages and disadvantages of each approach in order to identify the best practices that we will employ in our statistical analysis.

2.2. Empirical Research

There are few studies in the empirical literature regarding the factors affecting countries' attractiveness for mining investments. One of the critical limitations in conducting applied research on this subject is the availability of data. Much of the information regarding budgeted mining exploration expenditures is private and provided by third-party vendors.

[11] Otto (1992) identified nine investment criteria that are considered by international mining companies when they decide to invest in a particular jurisdiction. These are: 1) geological endowment, 2) the political characteristics of a country, 3) policies oriented to investment promotion, 4) regulatory frameworks applicable to mining, 5) the fiscal regime for mining, 6) policies that make easier the financing of mining projects, 7) environmental regulations and the social license to operate, 8) operational conditions for managing mines, and 9) project measures of profitability (like the net present value). According to the author, countries interested in fostering FDI in their native mining industries should enact and execute policies considering these nine criteria to improve their investment climate.

Khindanova's working papers (2005, 2006 y 2007) were the first studies dedicated to analyzing the relationship between exploration mining investments with variables measuring the geological potential and the investment climate in a country. These papers aim to measure the impact of the geological potential and the investment environment in the allocation of mining exploration expenditures using three types of econometric specifications: semi-log, log-linear, and truncated log-linear models. In all her models, the dependent variable was the logarithm of exploration expenditures of the country, and the independent variables were the geological potential and the investment climate.

She used the dataset from the Metals Economics Group's study "Corporate Exploration Strategies 2006,"[12] which compiled survey information of 1,624 companies that budgeted US$ 100,000 or more for exploration expenditures in 2006. She included 103 countries in her sample. The range of values for exploration expenditures is between US$ 100,000 and US$ 1.378 billion. Given the absence of reliable data to measure geological potential and investment climate, she proposed several proxies for these indicators.

Khindanova (2005, 2006) measured the geological potential using proxy variables related to the mining sector's participation in the economy of the countries included in her sample: share of mining exports in total exports, the participation of primary exports in total exports, and share of mining GDP on total GDP. The author also used indicators of the relative abundance of mineral endowments: mining production, mineral reserves, estimated mineral resources, land area, and the number of mining concessions granted in a country.

On the other hand, to measure the mining investment climate, Khindanova employed two proxies: The World Bank's Governance Index (WBGI) and the Index of Economic Freedom (IEF) elaborated by the Heritage Foundation and the Wall Street Journal. Her results showed that a good proxy for the geological potential of a country was its land area and that there were no essential differences in using IEF or WBGI (Khindanova 2005, 2007). In addition, her results showed that both the geological potential and the investment climate were significant determinants of the allocation of exploration investment budgets and that both variables were able to explain nearly 50% of the final allocation of exploration mining investments among countries (measured by the adjusted R^2 statistic). Those findings provided the first empirical support to the alternative view of mining competitiveness.

In another article, Khindanova (2011) extended her seminal work by including additional variables to her econometric specification. She considered GDP and population as additional independent variables to measure the effects of the size of local economies in the allocation of exploration budgets. Moreover, she introduced an interaction term (a nonlinearity) between the investment climate and the geological potential to control for the probable feedback effect between both variables. Her findings pointed out that neither GDP nor population was statistically significant to explain the allocation of exploration budgets across countries. Nevertheless, she found that the interaction term was statistically relevant, which is evidence of the existence of a nonlinear relationship among the exploration mining investment expenditures, the investment climate, and the geological potential.

Finally, Khindanova (2015) performed a sensitivity analysis to evaluate how sensible exploration expenditures were to investment climate variations. She conducted a separate study of different

[12] The Metals Economic Group was absorbed by SNL Financial Group in 2012. Later, SNL was acquired by Standard & Poor's (part of McGraw Hill Financial Group) in 2015, which now operates the S&P Global Market Intelligence platform.

types of exploration funding: a) total and grassroots exploration expenditures; b) budgets directed towards specific minerals exploration objective (such as gold, base metals, and diamonds); and c) expenditures divided by funding origin country. Her findings suggest that the sensitivity of exploration expenditures to investment climate depends on targeted minerals. For instance, a favorable investment climate attracts more of total and grassroots exploration for gold and base metals. Likewise, her analysis of the top three exploration funding countries showed that Canadian mining companies are sensitive to the investment environments in host countries. However, budget allocation decisions of Australian and UK companies were not related to the investment environments.

Therefore, Khindanova's key contributions are the following: a) the identification of the variables related to the alternative view of mining competitiveness, b) the formulation of an empirical econometric model that explains the allocation of mining exploration expenditures, c) the exploration of different measures of geological potential and investment climate, d) the identification of the existence of a nonlinear relation between the explanatory variables and the exploration investments expenditures, and c) the sensitivity analyses performed to evaluate the effect of the investment climate on several measures of exploration expenditures.

However, Khindanova's works also have limitations related to her econometric model’s foundations and the statistical analysis of her results. First, many of her model specifications are inflexible, not considering the process governing the decisions taken by exploration mining companies. As Jara (2017) pointed out, with an additive linear model specification, a country exhibiting a good investment climate, but with little or no mineral endowment, could still be capable of attracting capital for mining exploration. Likewise, a country with high geological potential, but with an extremely low investment climate, might obtain some exploration investment allocation. Both situations appear to be unreal. She did not perform enough analyses regarding the possible nonlinear relation among the variables incorporated in her econometric model’s functional form. Likewise, she did not perform econometric specification tests to see whether the equations employed were well specified.

Second, her econometric analysis shows that there is a least 50% of the exploration expenditures’ variance not explained by both the geological potential and the investment climate. This result means that other factors could explain the allocation of exploration expenditures across countries, and therefore Khindanova's results may be biased due to the omitted variables. Finally, Khindanova did not perform formal hypothesis tests regarding the traditional and alternative view of mining competitiveness, which would have required evaluating whether the marginal effect of the investment climate on exploration expenditures be greater than the marginal impact of the geological potential.

Building on Khindanova's previous articles, Jara (2017) provides new evidence regarding the linkages between geological potential and investment climate, and the allocation of non-ferrous mining exploration investment. In Jara (2017) , as in Khindanova's work, the dependent variable is the budgeted non-ferrous exploration investment, and the independent ones are the geological potential and the investment climate. Jara (2017) uses SNL (2014) data on budgeted exploration investment. Likewise, the geological potential is measured using the land area of each country as a proxy variable. The investment climate is measured by the Index of Economic Freedom, published by the Heritage Foundation (2014) and the Wall Street Journal. He works with a cross-country data set of 122 countries for the year of 2014.

The general specification of Jara's (2017) model is the following:

$$Pexpl_i = f\ (PLand_i,\ NIIEF) + \varepsilon_i\ , \tag{2.1}$$

where $Pexpl_i$ is the share of the country in the total exploration budget, $PLand_i$ is the country's share in the total land area of the countries included in the sample, *NIIEF* is the index of economic freedom of the country, and ε_i is the error term.

Given that the function f (•) relating the independent variables is an unknown multivariate function, the author proposes to apply a second-order Taylor expansion to find a good approximation. Then, equation (2.1) becomes:

$$Pexpl_i = \beta_0 + \beta_1\ PLand_i + \beta_2\ PLand_i^{\ 2} + \beta_3\ NIIEF\ + \beta_4\ \mathrm{NIIEF}^{\ 2} + \ \beta_5\ (PLand_i * NIIEF) + \ \varepsilon_i\ , \tag{2.2}$$

where β_i are the parameters to be estimated. Without counting the intercept of the equation (β_0), there are 32 possible combinations of the independent variables. After analyzing all of them, the author concludes that his better equations are the following:[13]

$$Pexpl_i = 0.002 - 1.6283\ PLand_i + 3.9267\ (PLand_i * NIIEF), \tag{2.3}$$

(2.018) (-7.39) (11.242)

$$\text{Adj. } R^2 = 0.7676$$

$$Pexpl_i = -0.0008 - 6.22328\ PLand_i^{\ 2} + 2.3458\ (PLand_i * NIIEF). \tag{2.4}$$

(-0.7438) (-6.5483) (14.359)

$$\text{Adj. } R^2 = 0.7508$$

While all the t-statistics (in parenthesis) and the adjusted R^2 in both equations have statistically good values, as Jara correctly points out: "those equations present a problem in terms of their economic foundations. The parameter for the geological potential [and its square in equation (2.4)] has an opposite sign with respect to what the theory and the common sense suggest." [14] (2017:68). To explain this result, the author proposes three possible explanations: a) the specification of the "true model" could not be the right one, b) the proxy variables selected could not be measuring the geological potential correctly or the investment climate of the countries, and c) there could be a structural break in the true model. Of the three possible explanations, the author only analyzes the last one. To do that, he proposes the following specification for the model:

$$Pexpl_i = \phi_o + \phi_1\ PLand_i * d_{\,x,\,i}\ +\ \phi_2\ PLand_i * NIIEF * (1 - d_{\,x,\,i}) + \ \varepsilon_i\ , \tag{2.5}$$

where ϕ_i are parameters to be estimated and $d_{x,\,i}$ is a dummy variable, through which he tests the existence of the structural break in the data. The dummy variable is defined as follows:

[13] In Jara (2017), those equations are B4 and B7, respectively.

[14] Equation (2.3) implies that the relationship between exploration investment and geological potential will be positive for countries with an index of investment climate (*NIEF*) greater than 0.41. Likewise, from equation (2.4), a similar conclusion is obtained, even though a quadratic curve represents the relationship between exploration investment and geological potential. In both cases, the most counterintuitive result is that the share on the exploration budget of a country (*Pexpl*) may have a negative value if it has a low "level" of investment climate (NIEF).

$$d_{x,i} = \begin{cases} 0 \; if \; NIEF_i < x, being \; 0 < x < 1, \\ 1 \; if \; NIEF_i \geq x, being \; 0 < x < 1. \end{cases} \tag{2.6}$$

The results obtained are the following:

$$Pexpl_i = 0.002 + 1.49 * PLand_i * d_{66} + 0.81 \, PLand_i * NIIEF \, (1 - d_{66}), \tag{2.7}$$

(2.02) (19.47) (7.6)

Adj. $R^2 = 0.77$

In this last equation, the t-statistics (in parenthesis) and the adjusted R^2 have statistically good values. Jara's main conclusion is that there is a threshold value of the investment climate of around 0.66, above which the mining competitiveness of a country is determined almost exclusively by its geological potential. Below it, investors take into consideration both the investment climate and the geological potential of the country to decide where to invest in mining exploration. A second important conclusion that arises from this last equation is that there is a constant term, even though with a low value, which is statistically different from zero, with a 95% confidence level. From this result, one may conclude that countries with low geological potential (small area) and low investment climate would still be able to attract mining exploration investment. This result seems to be unlikely. However, the constant term is maybe capturing the explanatory power of all the omitted determinants of mining exploration investment across countries such as social conflicts and population density.

Thus, in sum, Jara's (2017) results show that both geological potential and the investment climate are essential determinants of the countries' attractiveness for mining exploration investment. Likewise, based on his results, the author concludes that there seems to be a "threshold level" of the investment climate below which investors make the decision where to invest in considering both variables. However, Jara also points out that this result should be interpreted carefully since, in fact, that threshold is not a point. Instead, there is a kind of "transition zone" where the behavior of the investment climate progressively changes.

The next work that is worth mentioning is the thesis of Estrella et al. (2015). In their work, the authors begin replicating the empirical results obtained by Jara (2008) and Khindanova (2011),[15] but with one crucial difference: the use of an alternative proxy variable to measure the geological potential of the countries. Estrella et al. (2015) test the second argument made by Jara (2008, 2017) to explain the negative sign obtained by the variable that measures the geological potential. As we mentioned before, Jara (2008, 2017) points out that the election of the proxy variables could also explain this result. More precisely, he argues: "Country's land area and a general investment climate could be inefficient to capture all specificities of mining regulations and geological features of a jurisdiction" (2017: 69). He adds, "(…) the election of proxies for geological potential and investment climate was analyzed by Khindanova (2005, 2006). Nevertheless, it is recognized that further work should be made to deal with this issue in future studies" (Jara, 2017: 69).

In Estrella et al. (2015), the geological potential is measured by the gross value of mine production (*GVMP*), as Tilton and Guzman (2016) have recently proposed. This variable was chosen, considering that the mineral potential of a country should be related to its capacity to

[15] This study is a previous version of Jara (2017). In this last article, the author reports updated results.

produce mineral products. Therefore, countries with higher geological potential should have more massive flows of mine output, which in turn implies that they should have larger shares in the world mine production. While mineral reserves could also be considered as a good proxy for geological potential, the problem with the use of this variable is that it is not available for all countries. Besides, there is also a large variability on how this variable is defined and accounted for across countries. It is worth mentioning that there is another argument supporting the use of *GVMP* as a proxy to measure the geological potential, which is that there exists a strong positive correlation between mineral reserves and mining production (over 80%), as Tilton and Guzman (2016) have recently shown.

As in Jara (2008, 2017), Estrella et al. (2015) consider that the allocation of mining exploration investment across countries depends on the geological potential and the investment climate of the country, as stated in equation (2.1). Then, a second-order Taylor expansion is applied to equation (2.1), and it becomes equation (2.2), but with the only difference that the variable *Pland* is replaced by *%GVMP* as a proxy variable for geological potential. The following equation presents the change introduced:

$$Pexpl_i = \beta_0 + \beta_1\, \%GVMP_i + \beta_2\, \%GVMP_i^{\,2} + \beta_3\, NIIEF + \beta_4\, NIIEF^{\,2} + \beta_5\, (PLand_i * NIIEF) + \mathcal{E}_i\,, \qquad (2.8)$$

where *%GVMP* is the country's share of the total value of non-ferrous mine production of the countries in their sample.[16] In equation (2.8), as before, $Pexpl_i$ is the share of the country in the total exploration budget, *NIIEF* is The Index of Economic Freedom of the country, and $\mathcal{E}_i$ is the error term. Estrella et al. (2015) work with a cross-country dataset of 99 countries for the year of 2014.[17]

To illustrate the impact of using *GVMP* instead of the land area as a proxy variable for geological potential, we show in **Table 1** the results obtained by Jara (2017) and Estrella et al. (2015) for equations (2.2) and (2.8), respectively:[18]

[*This section is intentionally left blank.*]

[16] The gross value of non-ferrous mine production was provided by GĚRENS Graduate School (Priale,2015).

[17] The source of the data for the variables NIEF and *Pexpl* are the same as those of Jara (2017).

[18] In Jara (2017) the equivalent to equation (2.2) is equation E, and in Estrella el al. (2015) the equivalent to equation (2.8) is equation D. It is worth mentioning that Jara (2017) did not include equation E among his better equations, because he considers that it only reinforces the results obtained through equations (2.3) and (2.4), or B4 and B7 in his article.

Table 1: Results for Equations (2.2) and (2.8)

Equation (2.2) - Jara (2017)		Equation (2.8) - Estrella et al. (2015)	
β_o	0.0505	β_o	0.0896
	(1.9831)		(2.1668)
β_1 (*PLand$_i$*)	-0.836	β_1 (*%GVMP$_i$*)	0.9785
	(-2.2946)		(2.7363)
β_2 (*PLand$_i^2$*)	-2.9156	β_2 (*%GVMP$_i^2$*)	-6.8551
	(-2.1337)		(-6.2723)
β_3 (*NIIEF*)	-0.1873	β_3 (*NIIEF*)	-0.3302
	(-2.1681)		(-2.3641)
β_4 (*NIIEF^2*)	0.1704	β_4 (*NIIEF^2*)	0.296
	(2.3359)		(2.5238)
β_5(*PLand$_i$*)*(*NIIEF*)	3.0782	β_5 (*%GVMP$_i$*)*(*NIIEF*)	0.7145
	(6.8024)		(1.5466)*
Adjusted R^2	0.78	Adjusted R^2	0.76
N	122	N	93
Degrees of freedom	117	Degrees of freedom	87

Source: Jara (2017) and Estrella et al. (2015).

In these two equations, the t-statistics (in parenthesis) and the adjusted R^2 have statistically good values.[19] The main difference between these two equations is the negative sign of the variable that measures the geological potential obtained by Jara (2017). To show the differences of the results, we present **Figure 1 and 2**, which illustrate both equations in a plane, where the vertical axis measures the share of the country in the total exploration investment budget (*Pexpl*). In contrast, the horizontal axis measures the geological potential of the country (%GVMP). In both graphs, we draw the relationship between *Pexpl* and GVMP (%) for different levels of the investment climate.

In **Figure 1**, the relationship between (budgeted) exploration investment and geological potential has an inverted-U shaped form. Starting from a positive value, the share of the (budgeted) exploration investment of the country on the total exploration budget increases as the geological potential goes up, attains a maximum level, and then starts to decrease as the geological potential continues increasing. The point at which the dependent variable, Pexpl, reaches its maximum value depends on the level of the investment climate of the country. For instance, a country with a remarkably high investment climate, with an index of 0.9, would be able to obtain 13% of the total budgeted exploration investment if it also had high geological potential.[20]

From a theoretical point of view, the results shown in **Figure 1** are intuitively correct, but only in the zone in which the curve has a positive slope. Exploration investment increases with the geological potential of the country, and the amount of investment that the country will be able to attract will be higher if it has a better investment climate. What is counterintuitive is that after attaining a maximum level, the relationship between exploration investment and geological potential becomes negative. We obtain this result by using Estrella's et al. (2015)

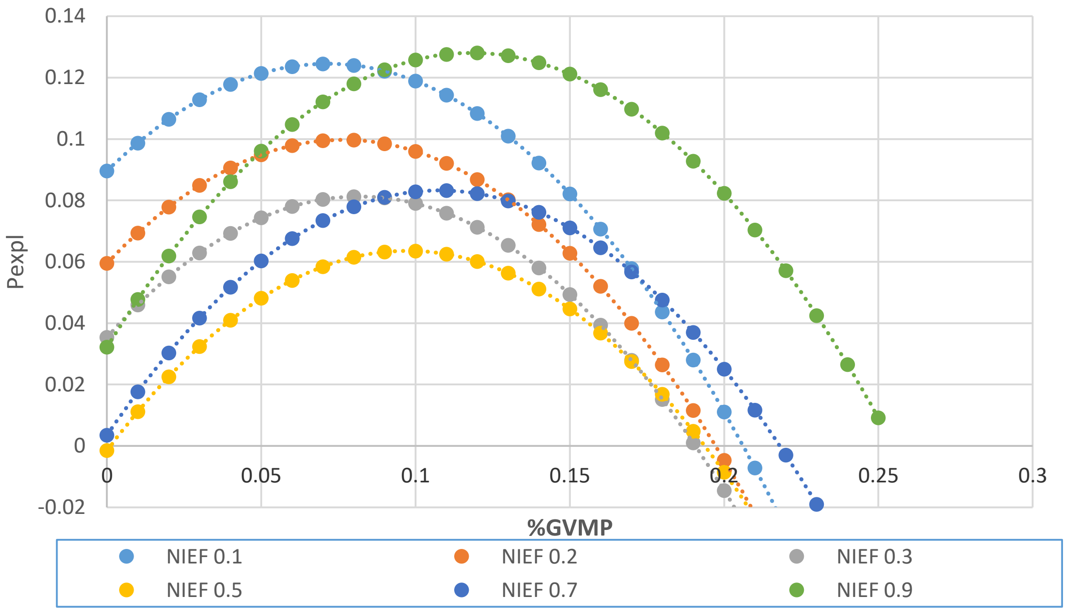
[19] Only the parameter β_5 in the Estrella´s et al. (2015) equation has a t-statistics slightly low. That parameter is statistically different from zero at a confidence level below 90% (around 85%).

[20] For instance, a value of 0.12 that represents the share of the country in the total value of non-ferrous mine production.

assumption of a functional form somewhat arbitrary: the one that arises after applying a second-order Taylor expansion to equation (2.1).

While it could be argued that in **Figure 1**[21] there are very few countries placed on the zone with a negative slope of these curves, it does not allow to conclude that the functional form of the equation that Estrella et al. (2015) use is the correct one.

Figure 1: Budgeted exploration investment (*Pexpl*) vs. geological potential (%GVMP)



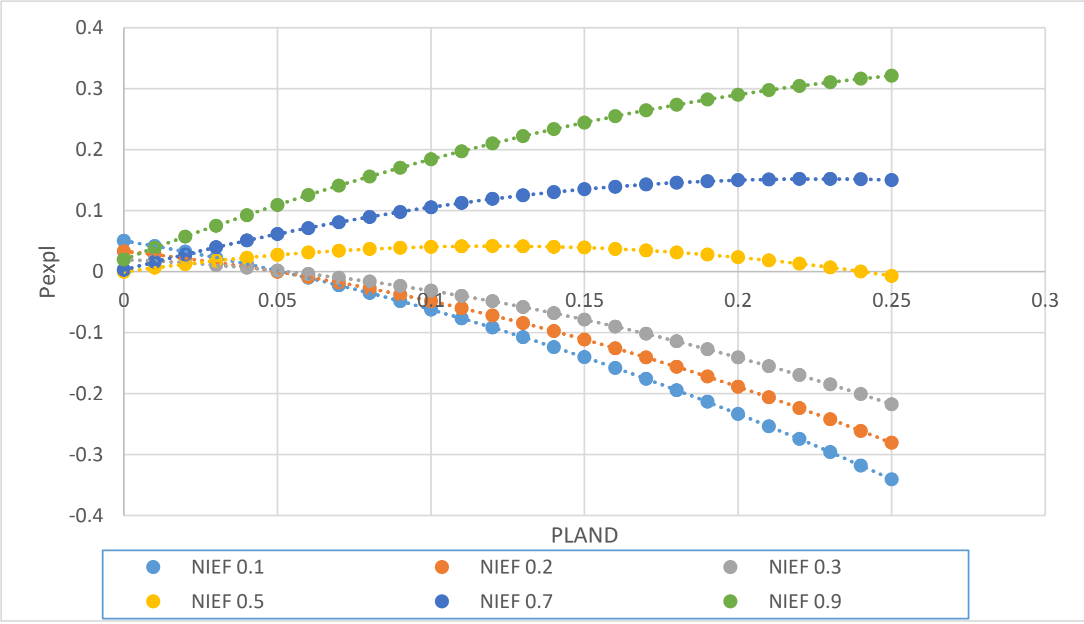
Source: Estrella et al. (2015). Own elaboration.

Figure 2 shows the similar results obtained by Jara (2017). In that figure, we observe that the relationship between exploration investment and geological potential is negative for countries with an investment climate index below 0.5. In the database, there are nine countries with an investment climate index (*NIEF*) below 0.5. Hence, the use of the land area as a proxy to measure the geological potential of the countries does not allow obtaining consistent results.

[*This section is intentionally left blank.*]

[21] There are only two countries, China, and Chile, placed on the zone with a negative slope of the curves. However, these two countries are the two most important producers in the non-ferrous mining industry.

Figure 2: Budgeted exploration investment (Pexpl) versus geological potential (PLand)

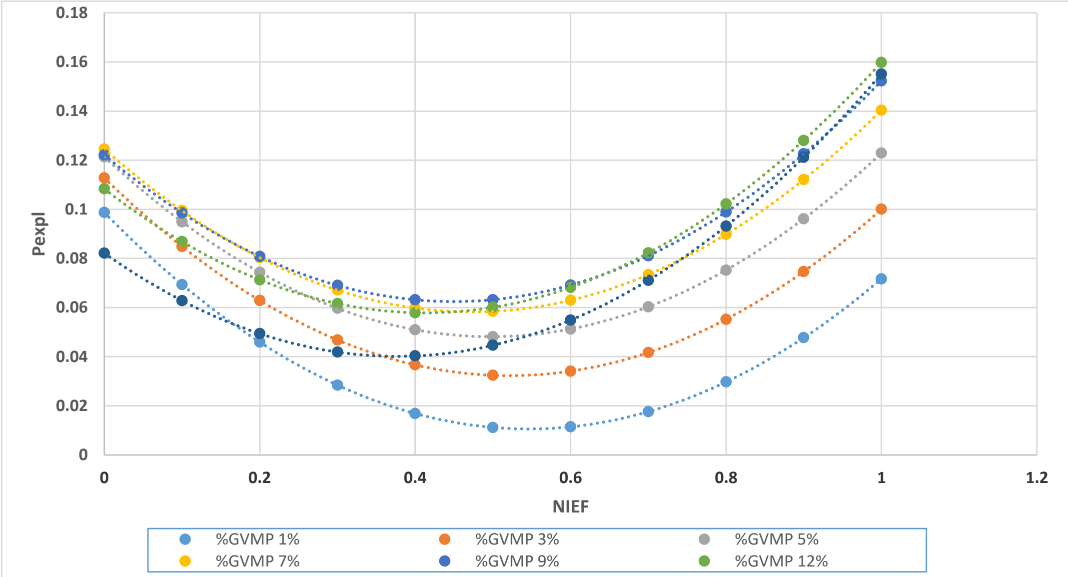


Source: Jara (2017). Own elaboration.

To complete the analysis, in **Figure 3** and **Figure 4**, both equations are drawn in a plane in which the vertical axis measures the share of the country in the total exploration investment budget (*Pexpl*). In contrast, the horizontal axis measures the investment climate (*NIEF*) of the country. Both figures depict the relationship between *Pexpl* and *NIEF* for different levels of geological potential. **Figure 3** shows the relationship between (budgeted) exploration investment and the investment climate has a U-shaped form. Starting from a positive value, the share of the (budgeted) exploration investment of a country on the total exploration budget diminishes as the investment climate increases, attains a minimum level, and then starts to rise as the investment climate continues increasing. The point at which the dependent variable, *Pexpl*, achieves its minimum value depends on the geological potential of the countries. Obviously, in this case, the zone of the curve with a negative slope does not provide intuitively correct results. In the graph, we can see that the curves attain their minimum values within a range that goes from 0.4 and 0.5 of the investment climate index (*NIEF*).

From a theoretical point of view, the results shown in **Figure 3** are intuitively correct only in the zone in which the curve has a positive slope: exploration investment increases with the investment climate of the country, and the amount of investment that a state can attract will be higher if its geological potential is higher with respect to other countries. As was mentioned for the case of **Figure 1**, the fact that the curve has a U-shaped form is the result of the assumption of a functional form somewhat arbitrary, which arises after applying a second-order Taylor expansion of Equation (2.1). In this case, again, it could be argued that few countries are placed in the zone with a negative slope of each curve in **Figure 3**, but that does not mean that the functional form proposed by Estrella et al. (2015) is the correct one.

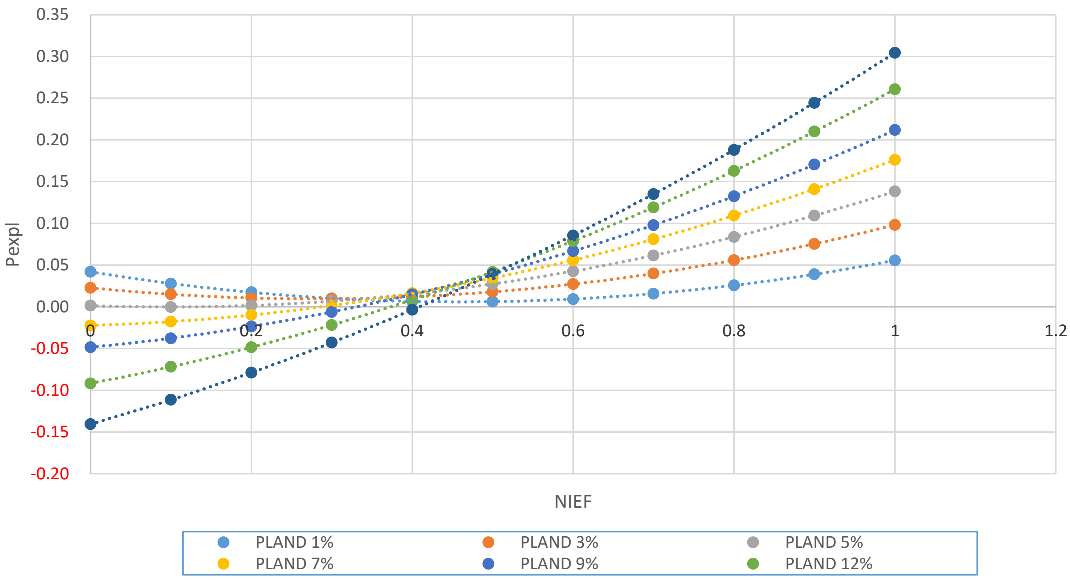
Figure 3: Budgeted exploration investment (Pexpl) vs. investment climate (NIEF)



Source: Estrella et al. (2015). Own elaboration.

Figure 4 shows similar results obtained by Jara (2017). In this case, the negative sign of the parameter β_1 makes negative the value of the dependent variable (*Pexpl*) for countries with a very high geological potential, but with low "levels" of investment climate, an outcome that seems to be inconsistent. Thus, comparing the results shown in **Figures 3 and 4**, one may conclude that the use of the land area of the country as a proxy for geological potential, instead of *%GVMP*, is what explains the negative relationship between exploration investment and geological potential obtained by Jara (2017).

Figure 4: Budgeted exploration investment (Pexpl) vs. investment climate (NIEF)



Source: Jara (2017). Own elaboration.

In sum, the evidence provided by Estrella et al. (2015) shed doubts on the existence of a structural break in the data, tested by Jara (2008, 2017). We will make a formal test of that hypothesis in **Section 5** of this article. Moreover, the results obtained by Estrella et al. (2015) support the hypothesis that there exists a nonlinear relationship between exploration investment, investment climate, and geological potential. Those results also allow concluding that the "true" functional form of the relationship among those variables cannot be obtained through a second-order Taylor expansion of equation (2.1). Finally, the results reported by Estrella et al. (2015) show that there is a constant term, significantly different from zero (with a confidence level of 95%), which means that there are some omitted independent variables in the specification of the model.

Taking this last result into account, Estrella et al. (2015) analyze some other possible determinants of the allocation of mining exploration investment across countries. The authors propose to consider two additional independent variables: social conflicts and the population density of countries. While the results reported in their thesis are not statistically very conclusive,[22] it is reasonable to think that there might exist a negative relationship among mining exploration investment, social conflicts (per squared Km), and population density. We will expand the analysis suggested by these authors with more detail in **Section 3** and **Section 4**.

A final work that is worth mentioning is Franazovic (2017). In his thesis, the author reports additional empirical evidence supporting the alternative view of mining competitiveness. Franazovic's study focuses on the location factors of exploration investment only for the case of copper. He works with a panel data of 12 countries, for the period 2000-2014. He obtains results that are in line with the ones already reported: exploration investment depends on the countries' geological potential and the investment climate. In his study, he measures geological potential through the countries' share in the total amount of the copper reserves. Moreover, the author measures the investment climate using two proxy variables: political stability and fiscal freedom.[23]

In conclusion, few empirical works in the literature deal with the analysis of the location factors affecting countries' competitiveness for mining investments. These studies identify that both geological potential and the investment climate have a significant impact on explaining how mining investors allocate capital in different jurisdictions. However, in our review, we have identified that the relation between exploration expenditures (as an indicator of mining competitiveness) and the location factors seems to be nonlinear and that there might be important omitted variables not considered in the analysis.[24]

The nonlinearity of the functional form has been modeled using several specifications, such as the quadratic approximation, the log-linear function, and the analysis of structural breaks in the data. The drawback of these approaches is that some of the results obtained are counterintuitive and could be biased. The empirical studies analyzed in this article have allowed researchers to make a vital leap ahead of our understanding regarding the factors affecting a country's mining competitiveness in recent years. Nevertheless, there is still a gap to be filled in

[22] Their test regression equation is flawed with an inadequate specification of its functional form.

[23] The Political Stability Index is provided by The World Bank's Worldwide Governance Indicators, whereas the Fiscal Freedom is one of the components of the Index of Economic Freedom published by the Heritage Foundation.

[24] This is the first argument mentioned by Jara (2017) related to the specification of the functional form of the "true model."

the literature because, as we have shown in this literature review, the studies have not adequately modeled the relation under study.

Based on the analysis conducted in this section, in the rest of the paper we will develop an alternative framework to model the relationship between exploration expenditures and the location factors. We propose an alternative way to modeling the functional form among the variables of interest that overcomes the limitations observed in the previous empirical studies, considering the recent developments in the empirical international trade literature. We also consider additional location factors to control for the problem of the omitted variable bias, as Estrella et al. (2015) has suggested: social conflicts and population density. In the next section, we describe our dataset.

3. Description of the data

This section describes the data on exploration expenditures as a proxy of mining competitiveness, the measures of geological potential, the investment climate, social conflicts, and population density. Moreover, it presents descriptive statistics for the variables we consider in our analysis.

The statistical information used in this article constitutes a cross-country database for the year 2014. It includes the following variables: total budgeted exploration expenditures by country as an indicator of investment attractiveness, the Index of Economic Freedom for every economy included in the sample, as a measure of investment climate, as well as the total gross value of mining production of non-ferrous metals, as a *proxy* of geological potential. This study also includes two control variables: population density (population per km^2) and the number of social conflicts per km^2.

The data on total budgeted expenditures for mining exploration by country[25] were collected from Estrella et al. (2015) and Franasovic (2017), who built a database containing information based on SNL (2014). The database includes exploration budgets in non-ferrous metals, diamonds, and radioactive minerals such as uranium.[26] The 124 countries considered in the study represented about 95% of total exploration budgets reported by SNL in 2014 (around US$ 11.4 billion).

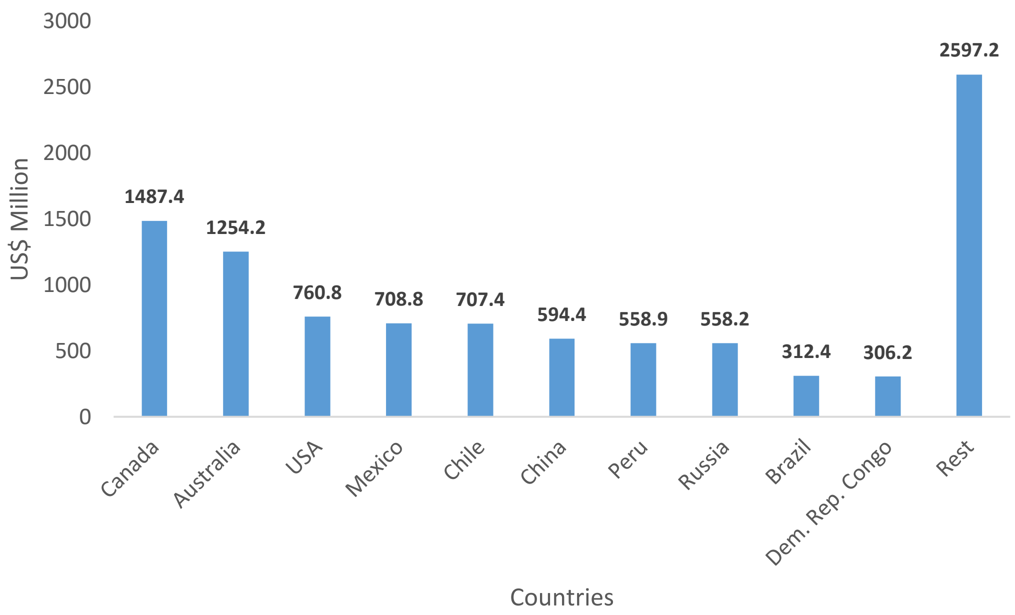
In our econometric analysis, we only examine 72 countries. We are not including some countries in our study, mainly because of a lack of data on the investment climate and social conflicts. The total exploration expenditures of the countries in our sample represent US$ 9,846 million, which accounts for 86.5% of the world's exploration budgets. **Figure 5** and **Figure 6** illustrate the distribution of the budgeted exploration expenditures for the top ten mining destinations, which account for 74% of the total world budget. Canada, Australia, and the USA

[25] Several authors have suggested the use of this variable as a measure of mining competitiveness, such as Khindanova (2007, 2011); Jara (2008, 2017); Jara, Lagos and Tilton (2008); and Estrella et al. (2015).

[26] The survey conducted by SNL was replied by approximately 3,500 mining companies engaged in exploration activities across the world. The study reported exploration budgets for 124 countries, which summed up to US$ 11.4 billion. Both Sudan and Greenland were not included in the survey due to their low representativeness in the sample. Greenland strictly is not a country, but a territory with restricted sovereignty. At the same time, Sudan in 2014 was not included in the Index of Economic Freedom of the Heritage Foundation and the Wall Street Journal, due to of its large internal social conflicts.

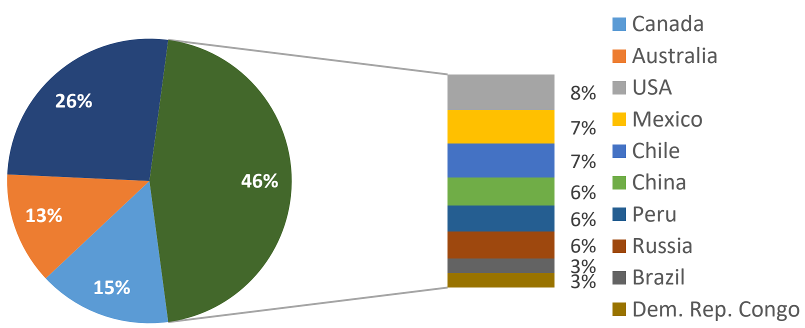
are between the top 3 destinations of exploration expenditures in the world, accounting for US$ 3,502 million, 54% of the budget of the top ten countries, and 36% of the total world budget in 2014. The rest 62 countries explain only 26% of the entire world budget.

Figure 5: Budgeted exploration expenditures for the top ten mining destinations (2014)



Source: SNL (2014), Estrella et al. (2015), Franasovic (2017). Own elaboration.

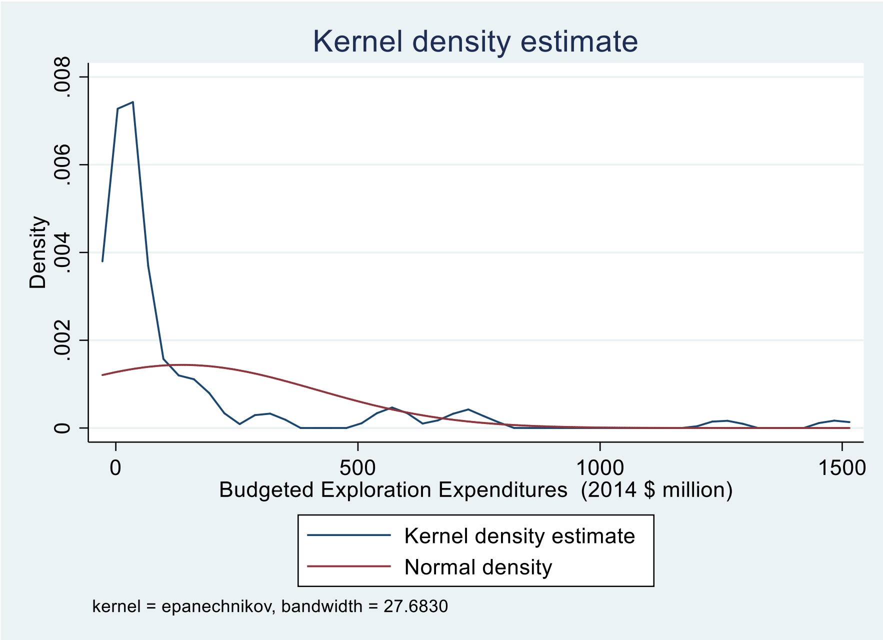
Figure 6: Budgeted exploration expenditures for the top ten mining destinations (2014)



Source: SNL (2014), Estrella et al. (2015), Franasovic (2017). Own elaboration.

The information we show in **Figure 5** and **Figure 6** indicates an asymmetric distribution of exploration expenditures. To corroborate that, **Figure 7** exhibits the kernel estimation of the probability density function of the budgeted exploration expenditures for the 72 countries. We include for comparison the graph of the normal density function. As we can see, the distribution of the total expenditures across countries is very skewed to the left (compared to the normal density, which is a symmetric function). This observation implies that a significant number of countries in the sample exhibited low exploration investments in 2014. The average expenditure in the distribution is $ 136.75 million, and the range of countries' exploration investments is between $ 100,000 and $ 1,487.4 million.

Figure 7: Kernel density estimate



Source: Own elaboration.

To deal with the non-linear and skewed nature of the exploration expenditures across countries, some authors propose to use a logarithmic function to model the relationship among variables.[27] We performed an analysis to evaluate whether a particular skewed probability distribution could have generated the exploration expenditures data. Using the Akaike Information Criterion (minimum AIC = 790.79) and the Kolmogorov-Smirnov test (p-value = 0.2620), we found evidence that the log-normal distribution fits well the data, so it seems that a logarithmic (non-linear) transformation could make sense. This result shows the first piece of evidence against the use of a quadratic approximation, as Jara (2008, 2016) and Estrella et al. (2005) propose. In Section 4, we will analyze in detail the issue regarding the functional form that can describe in a better way the behavior of exploration expenditures.

Regarding the measure of geological potential, we use the total gross value of mining production (GVMP), as Estrella et al. (2015), as well as Tilton and Guzman (2016), propose. The authors point out that the analysis of mineral potential should be related to the countries' ability to "produce" mineral commodities for export markets and domestic consumption. A country producing larger quantities of mineral production will likely attract investors looking for opportunities for developing new mining projects. The concept is related to the countries' capacity to generate flows of mine output, which are usually better measured by official statistical agencies. Thus, it means that jurisdictions with higher geological potential should

[27]The logarithmic transformation has been suggested by Khindanova (2007, 2011) to model budgeted exploration expenditures. Billington (1999), as well as Cheng and Kwan (2000), have used the log-transformation in their analysis of the foreign direct investment.

exhibit large flows of mine output. Therefore, they should have larger shares in the world mine production and should be more competitive to attract exploration investments (Tilton, 1992)

In contrast, the data on reserves, traditionally considered as a proxy of mineral endowment or geological potential, are not available for all countries and are still far from perfect. However, they have improved substantially over the last decades. The problem with using mineral reserves is the large variability on how it is defined and accounted across countries and, even worse, from one mine deposit to another. One additional argument in favor of using GVMP is the fact that Tilton and Guzman (2016) find a strong correlation between mineral reserves and mining production (over 80%). The authors point out that changes in countries' mineral reserves explain the most significant part of the variation in mining output among the top producing mining economies. Therefore, changes in the flows of GVMP should be directly and strongly associated with changes in the stocks of reserves.

The information about GVMP comes from a continuous study performed by GĚRENS Graduate School,[28] which monitors the evolution of the world mining industry each year. Based on that study, GVMP used in this paper considers only a subset of total mining production to make the variable compatible with the total budgeted exploration expenditures in non-ferrous metals published by SNL. GĚRENS obtains GVMP by multiplying the annual production of mining products (in terms of fine content) by the average yearly metal price obtained from official sources. GVMP only considers base metals (copper, zinc, lead, tin, nickel, and molybdenum) and precious metals such as gold and silver. We exclude from GVMP ferrous and platinum group metals.

It is worth noting that in the empirical literature on the subject of countries' mining competitiveness, authors such as Khindanova (2007, 2011) and Jara (2008, 2017) have used the land area as a *proxy* for the geological potential of countries. While intuitively, it is natural to postulate that countries with larger territories should have a higher mineral potential, the use of the land area as a proxy has some limitations. The most obvious is that it is a static variable not necessarily associated with the capacity of a country to produce flows of mine production, whereas geological potential evolves. As mining companies exploit mine deposits over the years, a country's mine production will eventually tend to diminish continuously until the depletion of mineral reserves. That is what happened, for instance, in several European countries. In the last decades of the Nineteenth Century, mineral production in the world started to shift from European countries to North America. Then, after several decades of exploitation of the mine deposits in USA and Canada, in the second part of the Twentieth Century, we observed another movement in the location of mine production in the world, this time from the USA and Canada to the South American countries, African jurisdictions, and Australia[29].

A second limitation of using the land area as a proxy for geological potential is that there are several large countries in which mine production is low or nil. Still, instead, oil and gas production is significant. Examples of this case are Algeria, Saudi Arabia, and Libya. The fact that a country has a vast territory does not necessarily mean that it has attractive mineral deposits.

---

[28] GĚRENS Graduate School processes information from the U.S. Geological Survey (*Mineral Commodities Summaries*, various numbers; *Historical Global Statistics for Mineral and Material Commodities*) and the British Geological Survey (*World Mineral Production*, *European Mineral Statistics,* and the *United Kingdom Minerals Yearbook*). The dataset is complemented by using information produced by the Chilean Commission for Copper (COCHILCO), and the local information produced by the ministries of mines (or equivalent institutions) of the countries in the sample. The dataset contains information for 123 countries, whose statistical agencies report mining production.

[29] See ICMM (2012) for further details.

Likewise, in any country, the relevant area is the one that is suitable to be eventually exploited economically by mining companies. This observation implies that urban areas, natural reserves, and any other restricted land territories should be subtracted from the country's land territory to measure its geological potential. Finally, the fact that Khindanova (2007, 2011) and Jara (2008, 2017) find that land area is a significant determinant of exploration investment probably has to do with the fact that there exists a low positive correlation between the size of the country's territory and the gross value of mine production (GVMP).[30]

The shortcomings mentioned before regarding the use of the land area as a proxy of geological potential probably explain the counterintuitive empirical results obtained in Jara's works (2008, 2018) as discussed in Section 2. In this article, we will show that the use of GVMP as an indicator of geological potential, instead of the land area, allows us to obtain better results.

On the other hand, to measure the investment climate, following Khindanova (2011, 2015) and Jara (2017), we use the Index of Economic Freedom (IEF), published by The Heritage Foundation and the Wall Street Journal[31]. This index seeks to measure the economic and institutional conditions of each country. The IEF for 2014 is determined by ten indicators related to characteristics of the business environment, which are the following: a) business freedom, b) government expenditure, c) monetary freedom, d) trade freedom, e) fiscal freedom, f) investment freedom, g) financial freedom, h) labor freedom, i) the quality of property rights and j) freedom from corruption. These ten indicators vary from 0 to 100 points, with higher values representing better economic conditions. The IEF is the average of the ten indicators; therefore, the index also shows values between 0 and 100. It is worth noting that the composite IEF indicator considers several determinants of foreign direct investment in the mining industry identified by Vivoda (2017), so we believe that the IEF is a good proxy of the investment climate for mining in a given country.

Finally, we consider two additional control variables in our analysis, considering the suggestion made by Estrella et al. (2015). First, we use the population density of each country in our sample to control for the fact that a country very populated will exhibit less available area for extractive activities. As mentioned before, a higher level of urbanization in a country introduces constraints to exploit mineral deposits, discouraging future exploration investments. Most of the data on countries' population comes from the World Bank's database *World Development Indicators 2014* (World Bank, 2014). The information about the countries' land area in km^2 comes from the Central Intelligence Agency's (CIA) publication *The World Factbook 2014* (CIA, 2014).

Second, we also consider the number of social conflicts per km^2 as a control variable. In the last decades in several countries, new mining projects have been delayed, or even canceled, due to the emergence of social conflicts.[32] As Grossman and Kim (1995), as well as Collier and

[30] The correlation between land territory and gross value of mine production, 0.44, is not as strong as the one that exists between mineral reserves and mine production (over 0.8, as was stated before).

[31] The Heritage Foundation (2014). Nowadays, the IEF is composed by twelve indicators, divided into four categories: rule of law (property rights, government integrity, and judicial effectiveness), government size (government spending, tax burden, and fiscal health), regulatory efficiency (business freedom, labor freedom, and monetary freedom), and open markets (trade freedom, investment freedom, and financial freedom).

[32]. For example, there are several cases in Peru, such as the Manhattan Company's Tambo Grande project in Piura, Bear Creek's Santa Ana mine in Puno, Newmont's Minas Conga in Cajamarca, and Southern Copper Corporation's Tia Maria project in Arequipa. Another relevant case is Barrick Gold's Pascua Lama project in Chile. In the USA, we observe the case of the Hope Bay and Pebble mine projects in Alaska.

Hoeffler (1998) point out, social conflicts create collateral damages to an economy because they generate external economic costs associated with the reduction of investments.

In this line of research, Huaroto and Vásquez Cordano (2015) found evidence that the occurrence of social conflicts in Peru between 2008 and 2012 generated a significant increase in the variance of the share price of mining companies listed in the Peruvian Stock Exchange. This effectively reduced the trading of those shares and inducing investors to "wait and see" how social conflicts evolve. Therefore, it is critical to control for the potential adverse effect of social conflicts in the attractiveness of a country to foster mining exploration investments. We obtained the number of social conflicts from the *Environmental Justice Atlas*[33] that accounted for 1,472 conflicts in May 2015 worldwide.

Table 2 summarizes the descriptive statistics of the variables used in this paper. Once we described our dataset, in the next section, we develop a new econometric methodology to analyze the relationship between budgeted mining exploration expenditures and its location factors.

Table 2: Summary Statistics of the Database

Variable	Label	Mean	Std. Dev.	Min	Max
Exploration Expenditures (US$ million 2014)	EE	136.75	277.32	0.10	1,487.40
Gross Value of Mining Production (million tons)	GVMP	4,800.50	10,287.48	0.40	57,316.63
Index of Economic Freedom	IEF	60.56	9.18	35.54	82.03
Number of Social Conflicts	SEC	17.30	28.86	1	199
Population (million people)	POP	79.67	218.99	0.8	1367.82
Land area (sq. km)	LAND	1,413,590	2,820,460	25,433	16,377,742
Social Conflicts per sq. km	SECD	0.000042	0.0000586	0.0000007	0.0003098
Population Density (pop. per sq. km.)	POPD	82.12	88.08	2.66	423.69

Source: CIA (2014), World Bank (2014), Estrella et al. (2015), Franasovic (2017), Heritage Foundation (2014), SNL (2014). Own elaboration.

4. Assessing the relationship between mining competitiveness and investment location factors

In this section, we propose a reduced-form econometric framework to properly analyze the relationship between mining exploration expenditures and the location factors described before, to test whether the data support the hypotheses about the "traditional" or the "alternative" view of mining competitiveness. As discussed in Section 3, the framework should consider our dependent variable's characteristics, "budgeted mining exploration expenditures"

[33] Available at https://ejatlas.org/ (last access: 05/08/2018).

illustrated in **Figure 7**. In other words, the model must be robust to the presence of a dependent variable exhibiting nonnegative skewed outcomes and sometimes values close to zero or equal to zero. In the next sub-section, we analyze the empirical problems related to estimating the econometric models that consider a dependent variable with such characteristics.

4.1. Econometric problems affecting the estimation of models that analyze the location factors for mining investment

We start our analysis here discussing the implication of observing zero or near-zero values in our dependent variable. The occurrence of zero values for exploration expenditures of mining companies (*EE*) means that mining investors have not allocated funds to finance exploration for new deposits in a specific country. A value close to zero indicates that a country in the sample has received little exploratory investment. Both results make economic sense since there are jurisdictions such as Singapore or Luxemburg where there is no mining activity given the size of their available territory. Moreover, according to SNL (2014), there are countries such as Bosnia, Thailand, or Albania that have attracted very tiny amounts of mining investment due to their little attractiveness in terms of geological potential and business climate. We use a *multiplicative functional form* to relate the dependent variable with the location factors proposed in Section 3 to control for this issue as follows:

$$EE_i = \beta_0 \cdot GVMP_i^{\beta_1} \cdot IEF_i^{\beta_1} \cdot SECD_i^{\beta_3} \cdot POPD_i^{\beta_4} \cdot \mu_i, \quad (4.1)$$

where GVMP represents the gross value of mining production; (IEF), the index of economic freedom; (SECD), the number of social conflicts per square kilometer; as well as (POPD), the population density. With the *multiplicative functional form*, the zero or near-zero observations in the dependent variable do not represent a problem for the estimation of this equation.

However, the presence of observations for which exploration expenditures are zero[34] or near zero introduces a problem when using the log-linear form of equation (4.1), as Khindanova (2011: 42) has proposed since the logarithm of zero turns to be $-\infty$, while the logarithm of small numbers produces large negative values. Both outcomes distort the classical estimation by ordinary least squares (OLS), making it infeasible. One alternative to deal with this problem is to drop the observations with zero values and estimate the log-linear form by OLS. Another way to tackle this problem is to estimate a truncated regression or a Tobit model (Khindanova, 2011: 42). However, these procedures can lead to inconsistent estimators of the parameters of interest, since imposing a truncation or censoring restriction in the estimation of the model when the dependent variable naturally exhibits zero or near-zero values constitutes a misspecification error (Silva & Tenreyro, 2006).

Another critical problem that we must address is the functional form to be used to estimate the relationship under study. As we have shown in **Figure 7**, the shape of the

[34] Zeros may also show up due to rounding errors to approximate exploration expenditures. Likewise, zeros may also appear because of missing observations that have been wrongly recoded as 0. The measurement errors generated by these two problems can also lead to inconsistent estimates.

distribution of the observations of exploration expenditures does not correspond to a linear relationship. Some studies have preferred to use the log-linear and semi-log forms (Khindanova, 2011, 2015), while others have chosen to use a non-linear approximation such as Taylor's expansion to deal with the observed nonlinearity. However, these studies have neglected the existence of Jensen's inequality (Jensen, 1906). This fact implies, for example, in the case of the logarithmic transformation that $E[\ln y] \leq \ln E[y]$. This expression means that the expected value of the logarithm of a random variable, *y*, differs from the logarithm of its expected value.

Hence, Jensen's inequality implies that using the ordinary least squares (OLS) method to estimate the parameters of a log-linearized equation and other non- linear equations could lead to obtaining very deceptive values for the elasticities (parameters of the equation) due to the presence of heteroskedasticity. We illustrate this problem using the following example. Suppose that we are interested in estimating by OLS the typical log-log model (the log-linearization of equation 4.1 as proposed by Khindanova, 2015) to explain the relationship between mining exploration expenditures (*EE*) and the location factors, as shown in the following equation:

$$\ln EE_i = \ln \beta_0 + \beta_1 \ln GVMP_i + \beta_2 \ln IEF_i + \beta_3 \ln SECD_i + \beta_4 \ln POPD_i + \ln \mu_i \qquad (4.2)$$

The statistical validity of the parameters to be obtained depends mainly on the assumption that μ_i and hence $\ln \mu_i$ are statistically independent of the regressors. Notice that the expected value of the logarithm of a random variable like μ_i depends on its mean and the higher-order moments of its probability distribution. Therefore, if the variance of the error component, μ_i, depends on $GVMP_i$ or IEF_i (which makes it heteroskedastic), then the expected value of $\ln \mu_i$ shall also depend on the regressors, violating the consistency of the OLS estimators.

The econometric literature has studied these problems extensively.[35] However, the studies that analyze the relationship between mining exploration investment and its location factors have not considered the potential bias of the elasticities estimated using the log-linear specification or other nonlinear approximations. This fact means that the models developed in the literature, in which the equations linking the variables are log-linearized or transformed by a nonlinear function, may exhibit severely biased parameters. The bias may be relevant for the comparative assessment of different theories regarding the factors affecting a country's ability to attract mining investments (the “traditional” vs. the “alternative view” of mining competitiveness), and for the evaluation of the effects of different public policies.

4.2. The Model

To deal with the problem related to the existence of a dependent variable, which may have observations with zero or near-zero values, and to determine the functional form of the equation, we propose a different approach. Given that the budgeted exploration expenditure data is very left-skewed, a linear or a 2nd order Taylor's expansion functional forms can provide

[35] See, for example, Goldberger (1968), Manning & Mullahy (2001), and Silva & Tenreyro (2006).

poor predictions since they restrict the effects of the regressors to be additive or quadratic. Instead, it is more reasonable to consider that the regressors have a multiplicative effect.

Following Silva & Tenreyro (2006), we propose the estimation of an exponential mean model and then use a pseudo-maximum likelihood (PML) estimation method to exploit our cross-sectional data. The proposed equation is the following:

$$EE_i = \exp(X_i\beta) + \varepsilon_i, \tag{4.3}$$

where $X_i\beta = \beta_0 + \beta_1 GVMP_i + \beta_2 EFI_i + \beta_3 SECD_i + \beta_4 POPD_i$. As explained before, the common practice of log-linearizing equation (4.3) and the estimation of parameters β by OLS is inappropriate for two reasons. First, EE_i can be zero or close to zero, making the OLS estimators infeasible. Second, even if all observation of exploration expenditures, EE_i, were positive, the expected value of the log-linearized error would depend on the covariates contained in X_i, so the OLS estimators will be inconsistent due to Jensen's inequality.[36] To clarify the point, we can express equation (4.3) as follows:

$$EE_i = \exp(X_i\beta)\mu_i,^{37} \tag{4.4}$$

where $\mu_i = 1 + \varepsilon_i / \exp(X_i\beta)$, so the error term is expressed in a multiplicative way. When the error term, μ_i, is statistically independent of X_i, the conditional variance of EE_i ($V[EE_i|X_i]$) and the variance of ε_i will be proportional to $\exp(2X_i\beta)$. Then, in general, ε_i will be heteroskedastic. This result implies that regressing $\ln EE_i$ on X_i (as it is the standard practice in the mineral economics literature reviewed in this paper) will lead to inconsistent estimates of β.[38] Therefore, it is not advisable to estimate β from a log-linear model. Instead, it is necessary to estimate the nonlinear model expressed in equation 4.3 in its original form. We need an estimator that can be consistent and reasonably efficient under different heteroskedasticity patterns and easy to estimate.

McCullagh & Nelder (1989), Manning & Mullahy (2001), as well as Silva and Tenreyro (2006) have proposed an estimator with such properties. They suggest estimating β by using a PML estimator based on some assumptions regarding the functional form of $V[EE_i|X_i]$. Among the different variance structures, the one considering the variance as being proportional to the conditional mean of the model is convenient. Hence, under this assumption, it is possible to

[36] A problem that arises because of Jensen's inequality is the fact that transforming our dependent variable by taking natural logarithm complicates prediction, since $\exp[E(\ln EE_i)] \neq E(EE_i)$.

[37] This structure is equivalent to the semi-log model, $\ln EE_i = X_i\beta + \ln \mu_i$, proposed by Khindanova (2015).

[38] In words of Silva and Tenreyro, "[i]t may be surprising that the pattern of heteroskedasticity and, indeed, the form of all higher-order moments of the conditional distribution of the error term can affect the consistency of an estimator, rather than just its efficiency. The reason is that the nonlinear transformation of the dependent variable […] changes the properties of the error term in a nontrivial way because the conditional expectation of ln[μ_i] depends on the shape of the conditional distribution of [μ_i] […] it is not possible to recover information about the conditional expectation of [EE_i] from the conditional mean on ln [EE_i], simply because ln[μ_i] is correlated with the regressors" (2006: 644).

state that $E[EE_i|X_i] = \exp(X_i\beta) \propto V[EE_i|X_i]$, and β can be estimated by solving the next set of first-order conditions (Cameron & Trivedi, 2009):

$$\sum_{i=1}^{n} [\,EE_i - \exp(X_i\beta)]\,X_i = 0. \tag{4.5}$$

The PML estimator based on equation (4.5) assigns the same weight to all observations given the assumption that the variance of the model is proportional to its mean. As Wooldridge (2010) states, the estimator obtained from equation (4.5) is numerically equivalent to the *Poisson pseudo-maximum likelihood* (PPML) estimator commonly used for count data. According to Silva and Tenreyro (2006), given the form of equation (4.5), the estimator of β will be consistent when the conditional mean is well specified, that is to say, when$E[EE_i|X_i] = \exp(X_i\beta)$.[39] This implies that the data do not necessarily have to be Poisson distributed at all, so the mining exploration expenditures do not have to be integer numbers for the estimator based on the Poisson likelihood function to be consistent and asymptotically normally distributed[40] (Gourieroux, Monfort, & Trognon, 1984; Cameron and Trivedi, 2009; Wooldridge, 2010). Since the assumption $V[EE_i|X_i] \propto E[EE_i|X_i]$ will not probably hold in practice, it is necessary to use a robust covariance matrix estimator, such as the one proposed by Huber (1965) and White (1980), to take into consideration the heteroskedasticity presence in the model (Cameron and Trivedi, 2009).

In order to verify the presence of the particular pattern of heteroskedasticity assumed by the PPML model (and the need to use a robust covariance matrix), it is possible to use the *test of overdispersion* proposed by Cameron & Trivedi (1990, 2005). According to the authors, a formal test of the null hypothesis of equidispersion, $V[EE_i|X_i] = E[EE_i|X_i]$, against the alternative hypothesis of overdispersion, can be based on the equation:

$$V[EE_i|X_i] = E[EE_i|X_i] + \alpha \cdot (E[EE_i|X_i])^2\,. \tag{4.6}$$

We can run a one-tail test $H_0: \alpha = 0$ against $H_1: \alpha > 0$ to evaluate the presence of overdispersion (more variance than the mean, which implies heteroskedasticity). We implement the test as follows. First, estimate the Poisson model, then construct the fitted value $\hat{\mu}_i = \exp(X_i\hat{\beta})$. Second, run an auxiliary regression of the generated dependent variable $y_i = \{(EE_i - \hat{\mu}_i)^2 - EE_i\}/\hat{\mu}_i$ on $\hat{\mu}_i$ without an intercept term, and apply a *t*-test of whether the coefficient of $\hat{\mu}_i$ is equal to zero. The test regression is the following:

$$y_i = \alpha\hat{\mu}_i + \vartheta_i, \tag{4.7}$$

[39] This is a desirable property of the generalized linear models (GLM). In fact, the Poisson model is equivalent to a GLM with a log functional link and the assumption that the data generating process that characterizes the dependent variable belongs to the Poisson distribution family (McCullagh & Nelder, 1989; Cameron and Trivedi, 2009, p. 322).

[40]. The Poisson PML estimator will be sufficiently robust to distributional misspecification other than the conditional mean (Silva and Tenreyro, 2006). This means that the PPML estimator will follow an asymptotic normal distribution (McCullagh & Nelder, 1989, p. 200), so we can apply to our model standard statistical tools to carry out hypothesis testing and inference.

where ϑ_i is the error term of the regression. It is important to note that the t-statistic for α follows an asymptotic normal distribution under the null hypothesis of no overdispersion (Cameron & Trivedi, 1990)

Therefore, the Poisson regression with a robust covariance matrix estimator presented in this section constitutes a practical framework to model the relationship among the mining exploration expenditures and their determinants. This econometric framework allows handling the problem of our dependent variable with zero or near-zero values. Moreover, it models the functional form of the link equation accurately, and it controls the issue of heteroskedasticity, assigning less weight to the observations in the sample with more significant variance without giving too much importance to observations more prone to contamination by measurement errors (which are not very informative regarding the curvature of the mean $E[EE_i|X_i]$).[41]

As a robustness exercise, we compare the results obtained through the Poisson regression with those obtained through the estimation of a linear regression equation, the semi-logarithmic, log-log, and Tobit equations, suggested by Khindanova (2011), as well as the results obtained by the estimation of the quadratic equation obtained through the second-order Taylor's expansion proposed by Estrella et al. (2015) and Jara (2008, 2017).

Likewise, we use the RESET test to check whether the specifications of the functional forms are valid (Ramsey, 1969).[42] To evaluate the presence of heteroskedasticity in the models estimated by OLS, we use the White test (White, 1980)[43] and the Breusch-Pagan test (Breusch & Pagan, 1980)[44]. We also test if the data supports Jara's (2017) claim regarding the hypothesis of the existence of a structural break in the data. A structural break can be understood as a subtle nonlinearity (Gujarati & Porter, 2009), so a formal test of it will provide additional information regarding whether a break is introducing instability in the functional form of the

[41] Cameron & Trivedi (2009: 558-561) and Wooldridge (2010: 740-742) explain that the Poisson regression with robust standard errors is a better alternative to a log-linear regression.

[42] The Ramsey RESET test evaluates the correct specification of the conditional expectation of a regression model, which is performed by checking the significance of additional regressors based on the powers of predicting the dependent variable (y) of the model. In our analysis, we include in the test regressions y^2 and y^3.

[43]The White test evaluates the existence of a constant variance by running an auxiliary regression, which regresses the squared residuals from the original regression model onto a set of regressors that contain the original ones along with their squares and cross-products. One then inspects the R^2. The Lagrange multiplier (LM) test statistic is the product of the R^2 value and sample size: $LM = n*R^2$, which follows a chi-squared distribution, with degrees of freedom equal to h-1, where h is the number of estimated parameters (in the auxiliary regression). In this article, we use the two-degrees-of-freedom particular case of the test (see Wooldridge, 2002: 127).

[44]The Breusch–Pagan test assumes that the error term is normally distributed under the null hypothesis, which implies that the score test statistic, S, is equal to the model sum of squares from the augmented regression with a set of regressor Z selected by the researcher and divided by 2. Under the null hypothesis, S follows a chi-squared distribution with m degrees of freedom, where m is the number of columns in matrix Z.

models. We run two tests for the OLS regressions: the CUSUM test developed by Brown, Durbin, & Evans (1969)[45] and the Supremum Wald Test developed by Andrews (1993).[46]

For the Tobit and PPML models, we also calculate the *link test specification statistic* (Linktest) to provide additional information regarding the correct specification of these functional forms, as suggested by Cameron and Trivedi (2009).[47] We used the software Stata 16 to process the data, and the results of our econometric analysis will be present in the next section.

5. Results

In this section, we present the results of the estimation of the Poisson PML model (PPML) to quantitatively assess the determinants of the allocation of mining exploration expenditures across countries.

5.1. Estimation results for the Poisson PML models

We ran different specifications of the model to verify the robustness of the estimation. **Table 3** summarizes the results.

[*This section is intentionally left blank.*]

[45] According to the authors, under the null hypothesis, the recursive residuals are shown to be independent and identically distributed following a normal distribution with 0 mean and constant variance. *The CUSUM of the recursive residuals* also has a mean of 0 under the null hypothesis. If the coefficients change after a certain time, the plot of the recursive CUSUM process will drift away from the expected value of 0. We use a test statistic based on the maximum of the recursive CUSUM statistic to evaluate the null hypothesis. A Brownian motion approximates the limiting distribution of the sequence of the recursive CUSUM statistic, so we use specific critical values in our analysis from the confidence intervals calculated by the authors.

[46] The Supremum Wald Test statistic is the maximum value of the test statistic that we obtain from a series of Wald tests over a range of possible break dates in the sample. The intuition behind the test is to compare the maximum sample test with what could be expected under the null hypothesis of no break.

[47] According to Cameron and Trivedi (2009), the *Linktest* is based on the idea that if a regression or regression-like equation is appropriately specified, you should be able to find no additional independent variables that are significant except by chance. One kind of specification error is called a *link error.* In regression, this means that the dependent variable needs a transformation or "link" function to relate the independent variables properly. The idea of a Linktest is to add an independent variable to the equation that is mostly likely to be significant if there is a link error. We implement this test by running an auxiliary regression where ones regress the dependent variable of interest, y, against the squared predicted dependent variable, $\hat{y}^2$. The test is based on the significance of the $\hat{y}^2$ using a conventional t statistic. The *Linktest* was originally proposed by Pregibon (1979).

Table 3: Estimation results of different Poisson PML model specifications

Dep. Var: Budgeted Exploration Expenditures	Model 1-PPML	Model 2-PPML	Model 3-PPML	Model 4-PPML	Model 5-PPML
VARIABLES					
Gross Value of Mining Production ($ 2013)	5.45E-05 ***	5.08E-05 ***	4.87E-05 ***	5.17E-05 ***	5.17E-05 ***
	(5.799)	(6.621)	(7.385)	(91.17)	(7.179)
Index of Economic Freedom		0.0488 **	0.050 ***	0.0351 ***	0.0351 **
		(2.444)	(3.194)	(33.63)	(2.216)
Social Conflicts Density (SC/km2)			-13,384 ***	-11,273 ***	-11,273 **
			(-2.590)	(-27.44)	(-2.170)
Population density (pop/km2)				-0.00579 ***	-0.00579 **
				(-26.00)	(-2.106)
Constant	4.351 ***	1.264	1.535	2.74 ***	2.74 ***
	(19.89)	(1.017)	(1.565)	(37.79)	(2.708)
Observations	72	72	72	72	72
Log-Likelihood	-6559	-5205	-4413	-3962	-3962
Pseudo-R^2	0.435	0.552	0.620	0.659	0.659
Squared Correlation	0.220	0.409	0.583	0.606	0.606
Chi^2 (significance of the model)	33.63 ***	55.38 ***	116.8 ***	15291 ***	139.1 ***
Akaike Information Criterion	13121	10415	8834	7934	7934
Ramsey RESET Test	40.11 ***	3.01 *	5.99 **	0.88	0.88
Linktest Specification Test (z-stat.)	-81.99 ***	-38.00 ***	-1.96 **	-0.17	-0.17
Test of Overdispersion (t-stat.)	1.87 *	3.07 ***	3.02 **	2.89 **	--

Robust z-statistics in parentheses for models 1, 2, 4 and 5. *** p<0.01, ** p<0.05, * p<0.1. Source: Own elaboration.

We start with Model 1-PPML, which considers the gross value of mining production (GVMP) as the only determinant of mining exploration investments. This indicator of geological potential is statistically significant and has a positive impact to explain mining competitiveness. This result is consistent with the "traditional view of mining competitiveness" (Tilton, 1983), which argues that the geological potential is a relevant driver of mining investments as the factor-endowment trade theory states. However, according to the RESET test and Linktest, the model is not correctly specified, which means that there are some omitted variables in this first equation. The adjustment of the model measured by the pseudo-R^2, and the squared coefficient of correlation (SCC)[48] are relatively low.

Then, we consider Model 2-PPML that incorporates into the first equation the Index of Economic Freedom (IEF). The specialized literature considers both variables as the critical location factors for mining investment (Khindanova, 2011, 2015; Jara, 2017). The incorporation of IEF allows us to evaluate whether the "alternative view of mining competitiveness" (Johnson, 1990; Tilton, 1992) also holds. We observe that both GVMP and IEF have a positive and statistically significant impact on mining exploration expenditures, so the investment climate is also an essential determinant of mining exploration investments. Nevertheless, despite that the

[48] The pseudo-R^2 reported in this paper is the McFadden's pseudo R^2 (Cameron & Trivedi, 2009). The squared coefficient of correlation between the fitted and observed values of the dependent variable is an alternative measure of the goodness of fit of the Poisson regression. A relatively high value indicates that the estimated model has a good explanatory power of the dependent variable (Cameron & Trivedi, 2009).

pseudo-R^2 and the SCC are higher with respect to the ones of Model 1-PPML, again, the RESET test and Linktest do not allow us to conclude that this model is correctly specified.

Then we incorporate two additional explanatory variables, which were suggested by Estrella et al. (2015): social conflicts per km^2 (social conflicts density, SECD) and population density (POPD). Model 3-PPML begins incorporating SECD as an explanatory variable; the estimation results show that the three variables, GVMP, IEF, and SECD are statistically significant. The variable SECD attains a negative sign, which implies that a larger number of social conflicts per km^2 would negatively affect the number of exploration expenditures allocated in a country. Although the model has appropriate goodness of fit, as measured by the pseudo-R^2 and SCC, the Linktest and RESET specification tests indicate that the model again is not correctly specified.

For this reason, we incorporate POPD in Model 4-PPML, observing that this variable has a negative sign, and it is statistically significant. This result corroborates what was argued in Section 3 regarding that a larger number of people living in a territory reduces the space available to perform mining extraction. The Linktest and RESET tests indicate that Model 4-PPML is correctly specified, and the goodness of fit of the model is the highest among the four models analyzed here. Besides, the model exhibits the minimum Akaike information criterion (AIC) of all the PP, which confirms that Model 4-PPML is an adequate specification to analyze the relationship between mining exploration investment and its location factors. However, one problem is a significant heteroskedasticity in the four models, as Cameron and Trivedi's overdispersion test indicates. Thus, we run an additional regression called Model 5-PPML, which is the same as Model 4-PPML. However, we use the Hubert-White consistent covariance matrix to correct the heteroskedasticity issue and obtain robust standard errors for the estimated parameters of the model.

As we can see in **Table 3**, Model 4-PPML has inflated z-statistics compared to those of Model 5-PPML, resulting from the overdispersion present in the data. In this context, one would tend to wrongly reject the hypothesis of a null effect of the location factors on the dependent variable more often in repeated samples. In contrast, Model 5-PPML incorporates the heteroskedasticity correction, which allows us to estimate parameters with much smaller z-statistics. After the correction, we still find that the estimated parameters are still statistically significant at 5% (for the case of IEF, SECD, and POPD) and 1% (for the case of GVMP).

Therefore, we can conclude that Model 5-PPML would be the best econometric model to analyze the relation among the location factors of mining investments and exploration expenditures. To confirm this proposition, in the next section, we will verify whether the Poisson specification is the adequate one.

5.2. Evaluating the Functional Form

In this section, we perform a robustness exercise to verify whether the chosen Poisson PML specification, Model 5-PPML, is the best to analyze the relationship among mining exploration expenditures and the location factors, compared to the other possible functional forms proposed in the literature.[49] As we discussed in Section 2, different authors have proposed alternative functional forms: linear model (Estrella et al., 2015); semi-log (Khindanova, 2011; Franasovic, 2017); log-log and Tobit models (Khindanova, 2011); as well as a quadratic approximation via a 2nd order Taylor's expansion (Jara, 2008, 2017; Estrella et al. 2015). We estimate the equations for these alternative specifications and compare them to our Poisson PPML model (Model 5-PPML), presented in the previous section. We report the results in **Table 4.**

First of all, the RESET test indicates that all alternatives functional forms (Model 1-SM, Model 2-SL, Model 3-LL, Model 4-TML, Model 5-TE1 y Model 6-TE2) are incorrectly specified to model the relationship between mining exploration expenditures and its location factors at a 5% and 1% significance levels. The Linktest also supports this result in the case of the Tobit model (Model 4-TML) at a 5% level. Based on these results, it is possible to affirm that the parameters estimated in all cases could be biased, so any conclusion based on these models may be misleading.

Second, the Breusch-Pagan and White tests confirm at 1% to 5% significance level the presence of heteroscedastic errors in these models, which implies the distortion of the standard errors of the parameters and, consequently, their t-statistics. This result adversely affects any statistical inference performed over these parameters. In the case of the semi-log model (Model 2-SL), the evidence of heteroskedasticity is weak, since only the White test confirms its presence at a 10% significance level. These findings corroborate the argument made previously regarding the need to apply a robust covariance matrix estimator to obtain valid standard errors and t-statistics for the parameters of a model to analyze the relationship of interest.

Third, we use the average variance inflation factor (VIF) of the regressors used in the model to evaluate whether there is evidence of multicollinearity. According to Gujarati & Porter (2009), an average VIF value of one for a set of regressors indicates that there is no multicollinearity in the estimation. As we can see in **Table 4**, only Model 5-TE1[50] and Model 6-TE2, obtained by a second-order Taylor's expansion, exhibit a very high degree of multicollinearity. This result implies that the t-statistics of both models are severely distorted, affecting any attempt to perform statistical inference. Likewise, both models exhibit estimated parameters that are very sensitive to adding or deleting variables, which means that the models are not stable. Lastly, the models have several redudant variables to explain mining exploration expenditures (i.e., the overparameterization of the model), so both models suffer from overfitting. We observe this result looking at the adjusted R^2 coefficients, which are very high with respect to the other models presented in **Table 4**.

[*This section is intentionally left blank.*]

[49] This exercise addresses the observation made by Jara (2017) regarding that the specification of the "true model" relating exploration mining expenditures and its location factors could not be the right one.

[50] Model 5-TE1 is like the selected model by Jara (2017, p.68) shown in Table 4 of his paper.

Table 4: Estimation Results of Different Functional Forms

Dep. Var: Budgeted Exploration Expenditures (EE)

Model Family	Simple Model	Log and Censored Specifications			Non-linear Specifications		PPML
Functional Form	*Linear*	*Semi-Log*	*Log-Log*	*Tobit*	*Crossed Effects*	*2^{nd} ord. Taylor*	*Poisson*
Estimation Method	OLS	OLS	OLS	ML	OLS	OLS	Robust PML
Model Name	Model 1-SM	Model 2-SL	Model 3-LL	Model 4-TML	Model 5-TE1	Model 6-TE2	Model 5-PPML
VARIABLES							
Gross Value of Mining Production (GVMP)	0.0176 ***	0.00011 ***		0.0168 ***	-0.000905	0.00698	5.17E-05 ***
	(8.198)	(6.107)		(10.71)	(-0.0489)	(0.404)	(7.179)
Index of Economic Freedom (EFI)	7.169 ***	0.00162		5.095 ***	2.402	-30.300 *	0.0351 **
	(3.042)	(0.0811)		(2.948)	(0.790)	(-1.869)	(2.216)
Social Conflicts Density (SECD)	-317,878	-2,282		-247,224	-429,625	-594,345	-11,273 **
	(-0.858)	(-0.728)		(-0.913)	(-0.158)	(-0.228)	(-2.170)
Population density (POPD)	-0.462 *	-0.0048 **		-0.384 **	0.297	0.509	-0.0058 **
	(-1.902)	(-2.311)		(-2.166)	(0.202)	(0.352)	(-2.170)
GVMP2						-3.67E-07 ***	
						(-3.455)	
EFI2						0.272 **	
						(2.013)	
SECD2						-7.474e+08	
						(-0.277)	
POPD2						0.00121	
						(0.765)	
GVMP * EFI					0.00058 **	0.000568 **	
					(2.238)	(2.321)	
GVMP * SECD					-544.9 ***	-460.8 ***	
					(-5.563)	(-4.844)	
GVMP * POPD					-0.000117 ***	-3.42e-05	
					(-2.841)	(-0.780)	
EFI * SECD					-5,624	12,781	
					(-0.126)	(0.310)	
EFI * POPD					-0.00897	-0.0172	
					(-0.395)	(-0.821)	
SECD * POPD					11,080 *	3,832	
					(1.983)	(0.654)	
ln(GVMP)			0.493 ***				
			(7.102)				
ln(EFI)			0.491				
			(0.462)				
ln(SECD)			-0.0588				
			(-0.440)				
ln(POPD)			-0.341 **				
			(-2.126)				
Constant	-330.5 **	3.227 ***	-1.175	-219.9 **	-94.100	848 *	2.740 ***
	(-2.301)	(2.655)	(-0.243)	(-2.088)	(-0.506)	(1.730)	(2.708)
Observations	72	72	72	72	72	72	72
Adjusted R^2	0.591	0.405	0.501	0.0879 +	0.790	0.825	0.659 +
RESET Test (F-stat.)	6.620 ***	12.620 ***	10.790 **	11.970 ***	6.130 ***	7.39 ***	0.880
Breusch-Pagan Heteroskedasticity Test χ^2	103.110 ***	0.190	16.800 **	--	94.44 ***	141.76 ***	--
White Heteroskedasticity Test χ^2	13.737 ***	5.047 *	12.608 **	--	10.962 ***	15.574 ***	--
Supremum Wald Test of Structural Break	9.302	7.935	16.904 *	--	0.504	--	--
CUSUM Residual Structural Break Test	0.493	1.112 *	0.880	--	7.176	--	--
Average Variance Inflation Factor (VIF)	1.060	1.060	1.27	1.060	68.490 ++	71.68 ++	1.060
Linktest (Specification Test, z-stat.)	--	--	--	-2.560 **	--	--	-0.170

z-statistics in parentheses for models 1, 2, 4 and 5. *** p<0.01, ** p<0.05, * p<0.1. + Pseudo R^2. Source: Own elaboration. ++ indicates a high degree of multicollinearity.

Fourth, concerning Jara's (2017) result about the existence of a structural break in the data, we used the Supremum Wald test and the CUSUM test to evaluate if the presence of a break is a valid hypothesis. As shown in 5, in all the models estimated by OLS, the tests support the hypothesis that there is no structural break affecting the stability of the models. There is less empirical support for this conclusion in the cases of Model 2-SL and Model 3-LL, given the weak statistical significance of the tests at the 10% significance level (the results of the tests contradict each other).

It was impossible to calculate the structural-break test values for Model 6-TE2, given the high multicollinearity in the regressors' matrix. However, we were able to find no evidence of a structural break in Jara's preferred functional form (Model 5-TE1). This empirical result is evidence indicating that the nonlinear and asymmetric nature of our dependent variable requires a different econometric treatment, like the one proposed in this paper.

Finally, comparing the robust Poisson PML specification (Model 5-PPML previously discussed) with the rest of the models presented in 5, we observe that our PPML model exhibits the best functional form among all. Both the RESET test and Linktest fail to reject the hypothesis that the Poisson model is correctly specified. Except for the overfitted models distorted by the strong multicollinearity, the PPML model exhibits high goodness of fit regarding the rest of the models.

In sum, the results of our robustness exercise allow us to conclude that there is strong empirical evidence to support the idea that the PPML model is the best functional form to model the relationships among mining exploration expenditures and the location factors considered in our analysis: GVMP, IEF, SECD, and POPD. The detection of heteroskedasticity in the models indicates that it is necessary to use a robust covariance matrix for the PPML model parameters, such as the one proposed by Huber and White. Lastly, we reject the argument that there is a structural break in the data affecting the stability of the model. A structural break is not behind the instability of the functional form; instead, it is the severely skewed nature of the exploration expenditures data exhibiting zero or near-zero values responsible for the nonlinearity in the model's specification. In contrast, our econometric results point out that the Poisson model developed in this article is the right solution for the type of data and the economic relationship we are interested in studying.

5.3. Calculation of the location factors' total and regional average elasticities

In the previous sections, we have determined that Model 5-PPML is the best econometric specification to explain the relationship between mining exploration expenditures and the location factors GVMP, IEF, SECD, and POPD. Given the nonlinear nature of the Poisson PML model, the coefficient values of Model 5-PPML shown in **Table 4** do not have a direct interpretation of economic importance. Nevertheless, it is possible to calculate total elasticities in the neighborhood of the means of the location factors. Since we employ the means of the explanatory variables, we call these computed values the *total average elasticities.* **Table 5** shows these elasticities.

Table 5: Total average elasticities of change in the location factors on mining exploration expenditures

Variables	Total Average Elasticities	Delta-method Std. Err.	Z-stat.	p-value	[95% Conf.	Interval]
Gross Value of Mining Production (GVMP)	0.25	0.04	7.18	0.000	0.19	0.32
Index of Economic Freedom (IEF)	2.13	0.96	2.22	0.027	0.25	4.01
Social Conflicts Density (SECD)	-0.47	0.22	-2.17	0.030	-0.90	-0.05
Population density (POPD)	-0.48	0.23	-2.11	0.035	-0.92	-0.03

Source: Own elaboration based on Model 5-PPML.

According to our results, GVMP and IEF become attractors of mining investment. We observe that GVMP exhibits a positive and statistically significant total average elasticity of 0.25. The effect of the geological potential on mining exploration investment is inelastic, which means that an increase in one percent of the geological potential in a country will induce an average change in budgeted mining exploration expenditures by 0.25%. In turn, the investment climate (measured by IEF) has a positive, statistically significant, and very elastic effect on stimulating the allocation of budgeted exploration expenditures in a specific jurisdiction. Per each one percent of improvement in the IEF indicator, the exploration expenditures assigned to a country would increase by 2.13%.

The discrepancy in the magnitudes of both elasticities would indicate that the investment climate is, on average, by far more relevant to attract mining exploration investments than the geological potential. Therefore, based on this result, one may argue that the promotion of good practices to manage geological information regarding mineral assets and foster geological surveys over the territory of a country is only one pillar to attract mining exploration investments. It is also fundamental to promote an attractive investment climate in a country to induce mining investors to allocate capital to explore and develop new mines.

On the other hand, our results indicate that both social conflicts (SECD) and population density (POPD) are *deterrents of mining investment*. SECD exhibits a negative and statistically significant elasticity, which implies that social unrest in a specific country disseminated over an area of territory constitutes a deterrent for investment since it increases the uncertainty regarding the possibilities to successfully develop and operate a mine and obtain a reasonable return on investment.

Likewise, this result is consistent with the findings of authors such as Imai & Weinstein (2000). They noted that social conflicts (like civil wars) can adversely affect the economic growth of a country because it diminishes private investment through a process of asset portfolio reallocation. Investors, facing uncertainty regarding the return of their mining investments, close positions on mineral assets, and invest in other alternatives outside the country. In case a social conflict escalates to all the territory of a country, it might severely damage the attractiveness for investment and, consequently, stop economic growth (Rodrik, 1999; Kang &

Meernik, 2005).[51] We observe that SECD has, on average, an inelastic effect: an increase of one percent in the numbers of social conflicts per km^2 generates a reduction of 0.473% in the amount of mining exploration investment allocated in a country.

Second, we observe that POPD also has a negative, inelastic, and statistically significant effect on mining exploration investments. On average, the elasticity of mining exploration investments with respect to population density is -0.48%. This result indicates that if the population density in a country is high, it is likely that the level of urbanization in this country be high as well, which implies that there is less area available to be granted as a mining concession. This situation could also be a deterrent for mining investment since mining companies could perceive that a highly populated country would exhibit fewer opportunities to access land areas for mining exploration and development.

In order to provide additional evidence regarding the effects of the location factors on mining exploration investment, it is possible to calculate regional average elasticities based on the disaggregation of our data per each region of the world: Asia, Latin America, Oceania, North America, Europe, and Africa. We report these elasticities in **Table 6**.

Table 6: Regional average elasticities of change in the location factors on mining exploration expenditures

	Location Factors							
Regions	**GVMP**		**IEF**		**SECD**		**POPD**	
North America	1.01	***	2.74	**	-0.05	**	-0.11	**
Oceania	0.53	***	2.37	**	-0.22	**	-0.58	**
Europe	0.12	***	2.28	**	-0.10	**	-0.51	**
Latin America	0.37	***	2.13	**	-0.70	**	-0.32	**
Asia	0.40	***	2.05	**	-0.16	**	-1.06	**
Africa	0.07	***	1.96	**	-0.23	**	-0.34	**

Source: Own elaboration based on Model 5-PPML. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Average elasticities calculated using the Delta Method. We order the regions by the value of the IEF elasticity. GVMP: Gross Value of Mining Production. IEF: Index of Economic Freedom. SECD: Social Conflicts per km^2. POPD: Population Density.

As we can see, there are differentiated effects of the location factors across world regions. For instance, North America exhibits a unit elasticity for GVMP, which means that a variation in the geological potential has a relevant impact on mining investment. This result is explained by the fact that the region contains the United States and Canada, countries with a long mining tradition and with transparent geological information systems. North America also exhibits the largest IEF elasticity, which indicates that countries in the region have the most favorable economic and political conditions to invest (Stedman & Green, 2018). A 1% improvement in the investment climate can generate a more than proportional positive impact on mining investments, estimated at 2.74%. Finally, the region exhibits the lowest elasticities for

[51] According to Rodrik (1999), the effect of an external shock on economic growth becomes more significant: the higher the number of latent social conflicts in a country and the weaker its institutions of conflict management.

SECD and POPD, which means that the increase of social conflicts over the territory and the rise in the population density has a minimal and inelastic negative effect on mining investments in this region. In the case of SECD, its effect is near zero. The region is very stable in terms of its institutional governance and political environment, which makes that social conflicts have a minimum impact on deterring mining investments (Przeworski & Curvale, 2006). Besides, the region contains some of the largest countries in the world. Therefore, a population expansion has fewer chances to crowd out mining investments due to the relative abundance of land area to be granted for mining exploration and development.

In the case of Oceania, we can observe that the elasticity of the geological potential on the level of investment in mining exploration is the second highest one after North America. This result is explained by the dynamics of the most relevant mining country in the region: Australia. This country is the one with the most significant territorial extension in the region and whose GDP represents about 82% of the continent (International Monetary Fund, 2019). Oceania also reports the second-highest IEF elasticity in the world because it has two of the six most open economies in the world (Australia and New Zealand) (The Heritage Foundation, 2018). Hence, a 1% increase in the IEF could translate into a rise of 2.37 % in mining exploration investments.

On the other hand, SECD elasticity is the third-lowest one (in absolute value) in the world. This result could be explained by the relief policies that Oceania has developed focused on generating jobs and developing local infrastructure (roads, water, and energy supply) (Mancini & Sala, 2018). However, despite relief policies, there are still regions, mainly in Australia, where the problem of income inequality remains latent, which is a potential driver of social conflict.

Finally, Oceania records the second highest POPD elasticity in the world (in absolute value) after Asia. Therefore, given a 1% increase in population density, the level of investment in mining exploration would reduce by 0.58%. The value of the region's POPD elasticity is mainly explained by Australia's internal migration demographic policy, aiming to decentralize its territory demographically (Cave & Kwai, 2019). Although population density is low, the number of dispersed reserves of native inhabitants in the Australian territory makes the population expansion difficult without affecting the potential land area available for mining activities.

In the case of Europe, we observe that the impact of GVMP on mining investments is the second most inelastic one within the regions. This result may happen because of the mineral resource depletion, as well as the little geological information available on the existing mining deposits in many countries of Europe (Stedman & Green, 2018). On the other hand, our elasticity calculations show that the SECD variable, unlike GVMP, has a significant deterrent effect on mining investment in the region since an increase of 1% would reduce almost proportionally the level of mining investment. In the specific case of Europe, this strong negative impact is not only associated with social and environmental conflicts but also with terrorist attacks, strikes for violation of labor rights, among others (Diario Olé, 2019).

Concerning the IEF variable, Europe exhibits the third-highest elasticity after the cases of North America and Oceania. This result could reflect the favorable economic and political conditions facing the countries in the region (18 of the 35 freest countries in the world are in this continent) (The Heritage Foundation, 2019). In that sense, an improvement of 1% in the investment climate may generate a positive and more than a proportional impact on mining exploration investments (estimated at 2.28%). Finally, POPD elasticity is the third most elastic one compared to the other regions because of the concentration of inhabitants in central

Europe. In that sense, mining companies will be careful when deciding whether or not to make investments in mining exploration, since these could be difficult to execute if the exploration areas were close to urbanized areas (Eurostat, 2019)

Another relevant case is the Latin American area, since this region has the third lowest GVMP elasticity in the world, surpassing only Africa and Europe. In that sense, given a 1% increase in geological potential, mining exploration investments would only increase by 0.36%. However, according to the Fraser Institute, Latin American countries such as Argentina, Chile, and Peru show a higher rating in the index of best practices in minerals, which has allowed Latin American geological potential to be recognized internationally (Stedman & Green, 2018). On the other hand, the IEF elasticity is the third most inelastic in the world, mainly due to the tax and regulatory burden, and the absence of improvements in the mining policies of countries (Melguizo, 2017).

Latin America also exhibits the second highest SECD elasticity (in absolute value) compared to those calculated for the other regions. Although there have been advances in transparency standards in extractive industries, legal loopholes have allowed the mismanagement of natural resources, rising environmental costs, and increasing the number of social conflicts as well as anti-mining movements. On the other hand, the tension between peasant communities and mining companies for environmental pollution issues is occurring more often in the region (Kaufman, Robinson, & Cruz Vieyra, 2019). Finally, POPD elasticity exhibits the second lowest value among the elasticities calculated for the other regions. Hence, a 1% increase in the POPD variable would only contract the level of mining investment by 0.33%. This result is plausible because the region includes three of the world's largest countries (Brazil, Argentina, and Mexico). Thus, a population expansion is less likely to displace mining investments due to the relative abundance of land area.

In the case of the Asian continent, we observe that the GVMP elasticity exhibits the third most elastic value compared to the ones estimated for the other regions. Thus, given a 1% increase in geological potential, mining investment in the continent would experience a positive impact of 0.40 %. This result can be explained by the fact that the Asian region includes China, the world's largest gold producer (Gold Hub, 2019), and the third largest copper producer (Garside, 2019).

However, in the case of the investment climate, Asia has similar elasticity to Africa due to the high government intervention in the Asian countries as it is in the case of North Korea (The Heritage Foundation, 2019). The direct consequence of this situation is that internal social conflicts do not significantly impact the decisions of public policy made by the central government, explaining why the SECD elasticity of Asia is the second most inelastic one in the world. Thus, given a 1% increase in SECD, mining investment would reduce by only 0.16%. Finally, contrary to the previous variable, the POPD elasticity is the one exhibiting the highest magnitude (in absolute value), because this continent hosts approximately 60% of the world population.[52] Therefore, any population growth would displace mining investments due to the relative scarcity of land area available for mining exploration and development.

Like Latin America, Africa is another interesting case study because it shows the lowest GVMP elasticity relative to the ones estimated for the rest of the regions analyzed. This result could be explained because the quality of the African geological information has a low quality, which contributes to reducing the attractiveness of Africa for mining exploration investments (African Minerals Development Centre, 2017). Africa also exhibits the lowest IEF elasticity. Thus, in the face of a 1% improvement in the investment climate, the level of mining investment only would increase by 1.96. This result is reasonable, taking into account that about 90% of African countries are considered “little free” (The Heritage Foundation, 2019). Besides, despite having improved some macroeconomic indicators, African countries still have high public debt and inefficient state companies that have reduced the global competitiveness of the region.

Finally, Africa exhibits low elasticities for SECD and POPD. This outcome implies that the increase in social conflicts in the territory and the expansion of the population have a moderate to a mildly negative effect on mining investments. In the case of SECD, its impact is small and inelastic because several African countries live under the oppression of military governments, and social protests mostly do not achieve their objective (Idean, et al., 2012). Besides, the region has a population density of 43.7 inhabitants per square kilometer, which is the second-highest worldwide after Asia (Population Pyramid, 2019). However, a population expansion would not be a decisive driver for displacing mining investments since urban areas are not close to mining exploration and exploitation zones.

To sum up, the statistical results of regional average elasticities based on the Poisson PML model show that both GVMP and IEF constitute significant attractors of mining exploration investments in all the regions. At the same time, SECD and POPD represent relevant deterrents to invest in mining exploration. Although the impact of these drivers differs from region to region, the sign of these variables is consistent with previous findings in the literature. Regarding GVMP and IEF, the results obtained allow us to support both views of mining competitiveness. To further analyze this outcome, in the next section, we formally test whether there is a statistical difference between the effects of the alternative and traditional views on mining exploration expenditures.

5.3. Testing the “alternative view” against the “traditional hypothesis” about mining competitiveness

In this section, we statistically evaluate if the investment climate of a country is a more relevant driver to attract mining exploration investments than its geological potential. As we explained in Section 2, this hypothesis reflects the “alternative view of mining competitiveness (Johnson, 1990; Tilton, 1992).[53] This proposition states that a favorable business climate is a more important factor for the competitiveness of a country to attract new investment in the mining sector than the geological potential.[54] Using Model 5-PPML and its estimated elasticities, we contrast both the “alternative and traditional views” of mining competitiveness hypotheses by using one-tail Wald tests to evaluate the following statistical statement:

$$H_0\colon e_{IEF} > e_{GVMP} \quad vs \quad H_1\colon e_{IEF} = e_{GVMP},$$

[53] To the best of our knowledge, it is the first time that the alternative view of mining is formally tested in the literature.

[54] The geological potential has been traditionally considered as a main driver of mining competitiveness based on the factor endowment trade theory.

where e_{IEF} is the investment climate elasticity and e_{GVMP} is the geological potential elasticity. **Table 7** shows the result of the test.

Table 7: One-tail test to evaluate the alternative view of mining competitiveness hypothesis considering all the sample of countries

Null Hypothesis: Elasticity [IEF] > Elasticity [GVMP]	
Chi2	3.7
p-value	0.973

Source: Own elaboration based on Model 5-PPML.

The test indicates that we fail to reject the hypothesis that the investment climate has higher elasticity that the geological potential, which statistically supports the alternative view of mining competitiveness for all our sample of countries. We can also test the hypothesis across the six regions of the world described in the previous section. We report the results of this analysis in **Table 8**.

Table 8: One-tail tests to evaluate the alternative view of mining competitiveness hypothesis across world regions

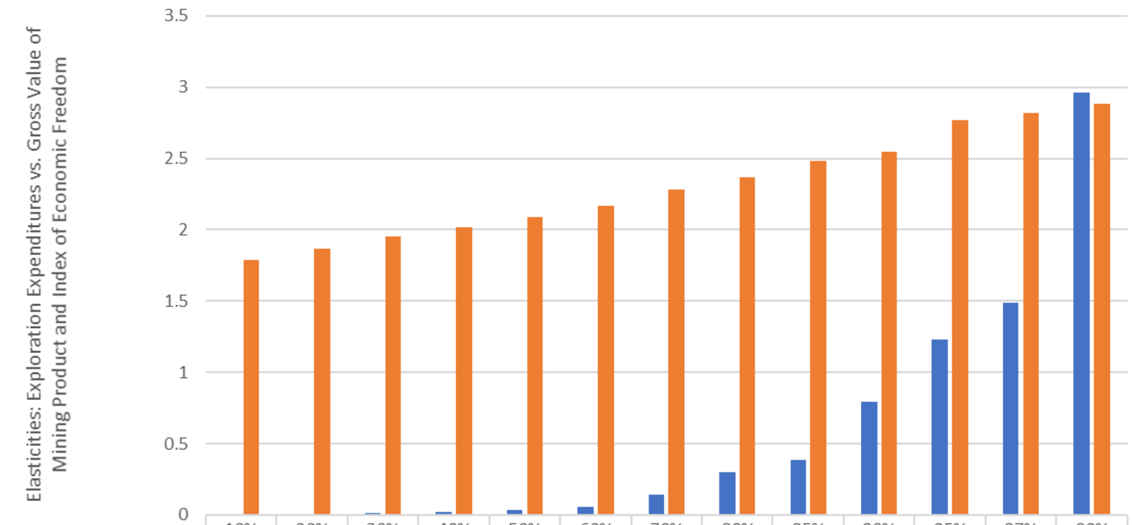
Null Hypothesis: Elasticity [IEF] > Elasticity [GVMP] across regions		
Variables	Chi2	p-value
Asia	2.99	0.958
Latin America	3.19	0.963
Oceania	2.78	0.952
North America	1.75	0.907
Europe	4.36	0.982
Africa	4.50	0.983

Source: Own elaboration based on Model 5-PPML.

Again, we fail to reject the null hypothesis. Therefore, our results indicate that the investment climate has a larger impact than the geological potential in all the regions considered in this study. Hence, the alternative view of mining competitiveness holds in all the world regions analyzed in this study.

Finally, given the asymmetric distribution of mineral exploration expenditures across countries identified in Section 3, it is likely that the location factors such as the geological potential and the investment climate exhibit differentiated effects over the allocation of mining exploration investment worldwide. We compute the GVMP and IEF elasticities per quantile of the exploration expenditures distribution. **Figure 8** shows the results of this calculation.

Figure 8: Elasticities concerning the investment climate and geological potential calculated over the quantiles of the mineral exploration expenditures distribution



	10%	20%	30%	40%	50%	60%	70%	80%	85%	90%	95%	97%	99%
elasticity EE/GVMP	0.001	0.004	0.015	0.020	0.033	0.059	0.139	0.301	0.382	0.791	1.232	1.490	2.964
elasticity EE/IEF	1.785	1.869	1.952	2.014	2.088	2.170	2.279	2.371	2.485	2.544	2.767	2.818	2.883

Quantiles

Source: Own elaboration based on Model 5-PPML. Average elasticities are computed using the Delta Method.

We observe that the non-linear and asymmetric nature of the distribution of mineral exploration expenditures generates differentiated effects of the investment climate and the geological potential on mining competitiveness. The geological potential has a negligible impact on stimulating exploration expenditures in countries receiving little investment, which are dispersed around the first five deciles of the distribution. In this case, only the investment climate has an elastic effect on attracting mining exploration expenditures. The geological potential starts to have a relevant but inelastic effect from the sixth decile. This result means that in countries with a moderate to a high level of mining investment, the geological potential becomes more relevant as an attractor of mining investment. It is only over the quantile 95% of the distribution that the geological potential has an elastic effect over mining investment. Despite the amount of investment allocated over the distribution of this variable, the investment climate is always an important factor in stimulating the allocation of exploration expenditures in a country.

To statistically confirm the finding shown in **Figure 8**, we run one-tail Wald tests to evaluate whether the IEF elasticity is greater than the GVMP elasticity across the quantiles of the exploration expenditures distribution. We present our results in **Table 9**.

Table 9: One-tail tests to evaluate the alternative view of mining competitiveness hypothesis over several quantiles of the distribution of the mining exploration expenditures

	Null Hypothesis: Elasticity [IEF] > Elasticity [GVMP]	
Quantiles	Chi2	p-value
10%	4.9	0.987
20%	4.88	0.986
30%	4.82	0.986
40%	4.79	0.986
50%	4.73	0.985
60%	4.61	0.984
70%	4.25	0.980
80%	3.60	0.971
85%	3.36	0.967
90%	2.11	0.927
95%	1.32	0.874
97%	0.92	0.832

Source: Own elaboration based on Model 5-PPML.

As we can see in **Table 9**, we fail to reject the null hypothesis about the validity of the alternative view of mining competitiveness for all the selected quantiles of the distribution of mining exploration expenditures. These results mean that the investment climate is a strong attractor of mining exploration investment and constitutes a significant driver of a country's mining competitiveness. The geological potential has a lower effect as an attractor of mining exploration investment in a particular jurisdiction, independently of the countries' location over the distribution of the exploration expenditures. Therefore, this analysis allows us to find that there exists an asymmetric effect of both explanatory variables to determine the number of exploration expenditures allocated in each group of countries over the distribution.

5. Conclusions

Over the past fifteen years, studies on the determinants of countries' competitiveness to attract mining investments have shown favorable empirical evidence to support the hypothesis of the "traditional view of mining competitiveness," which argues that geological potential is an essential determinant of a country's attractiveness for mining investments. This hypothesis is based on the theory of comparative advantage of international trade.

However, empirical evidence on the "alternative view" of mining competitiveness, which establishes the importance of a country's investment climate as a mining investment attractor, remains insufficient and scarce. Therefore, following the line of the research proposed by Jara (2017), this article assesses the validity of the "alternative view" hypothesis regarding the determinants of mining competitiveness. Likewise, we incorporate two additional variables in the analysis: i) social conflicts and ii) population density.

First, the paper makes an extensive review of the literature on the determinants of mining competitiveness. It finds that the existing empirical works on the subject present certain methodological limitations since they did not conduct an adequate study on the behavior of the mining exploration expenditures as a dependent variable (which is a proxy variable for mining competitiveness). Through a descriptive analysis of cross-sectional data, the use of the Akaike information criterion (AIC), and the Kolmogorov-Smirnov test, this paper demonstrates that mining exploration expenditures would follow a log-normal, skewed distribution toward the left. We observe this result since many countries in the sample exhibit low mining exploration expenses. For that reason, the use of a quadratic equation, as in Jara (2008, 2017) and Estrella et al. (2015), leads to obtaining biased estimates for the parameters of the determinants of mining competitiveness.

Second, after identifying the problem of the distribution of exploration expenditures, we develop a new econometric framework to adequately analyze the relationship between mining exploration expenditures and their location factors. We estimate a Poisson model with exponential mean and use the Pseudo-Maximum Likelihood (PPML) method to obtain the parameter estimates. We show that the budgeted mining exploration expenditures (EE) by country are not only determined by the geological potential (GVMP), as the standard theory of international trade suggests. Variables such as the investment climate (IEF), social conflicts (SECD), and population density (POPD) are also critical factors that affect this variable.

We also conduct a robustness analysis through the estimation of five econometric PPML models with different specifications. The results of the Linktest, the RESET test, and the Akaike information criterion (AIC) show that the equation with the best specification and goodness of fit is Model 5-PPML. This model incorporates our four explanatory variables (GVMP, IEF, SECD, and POPD) simultaneously and corrects the problem of heteroscedasticity through the consistent covariance matrix of Hubert-White. Our results show that both the geological potential (GVMP) and the investment climate (IEF) have a positive and significant impact on the level of mining exploration investment. In contrast, social conflicts (SECD) and population density (POPD) have a negative and significant effect on that variable.

Third, we carry out a second robustness exercise to assess whether the functional form proposed in the paper (Poisson PML) is appropriate to analyze the relationship between investment in mining exploration and the determinants of mining competitiveness. We compare the PPML specification with other functional forms previously explored in the literature. Previous research works have proposed alternative functional forms, such as the linear, semi-log, log-log, and Tobit models, as well as a quadratic equation obtained through a second-order Taylor expansion.

Based on the analysis performed and the results of the Linktest, RESET test, Breusch-Pagan, White tests, and the calculation of the variance inflation factor (VIF), we show that the PPML model is the best functional form to model the existing relationship between exploration expenditures, as a proxy variable for mining competitiveness, and its determinants: GVMP, IEF, SECD, and POPD. Similarly, the hypothesis sustaining the existence of a structural break in the data that determines a “threshold area for the investment climate” is rejected. The asymmetric distribution of the budgeted mining exploration expenditures data (with a significant amount of values close to zero on the left side of the distribution) makes it necessary to use a nonlinear model.

Fourth, we calculate the total and regional average elasticities of the determinants of mining exploration investments. We find that GVMP and IEF are fundamental determinants of mining exploration investment. The average elasticity of mining exploration expenditures with respect to geological potential (GVMP) is a positive, inelastic, and statistically significant, with a value of 0.25. In turn, the average elasticity of mining exploration expenditures with respect to the investment climate (IEF) is positive, elastic, and statistically significant, with a value of 2.13. The discrepancy in the magnitudes of both elasticities allows us to argue that the investment climate is, on average, much more relevant to encourage mining exploration investments than the geological potential.

On the other hand, we find that the average elasticity for social conflicts (SECD) is negative, inelastic, and statistically significant, achieving a value of -0.47. Likewise, the average elasticity for population density (POPD) is negative, inelastic, and statistically significant, exhibiting a value of -0.48. These results allow us to assert that both social conflicts and population density are variables that deter investments in mining exploration.

The PPML model also allows us to calculate the elasticities of the determinants of mining exploration investment by region of the world. Our results show that the region that would benefit the most from a 1% increase in its geological potential (GVMP) would be North America since it exhibits the highest elasticity among all the regions considered in our study. In contrast, Africa would be the opposite case since it has an elasticity of 0.07. In this region, a 1% increase in its geological potential would only increment the region's capability to attract mining investments by 0.07%. We observe the same pattern in the case of the investment climate (IEF). Thus, given a 1% improvement in IEF, the level of mining exploration investment in North America would increase by 2.74% (the highest elasticity value for IEF observed in all regions). In contrast, in Africa, an increase of 1% in the IEF indicator would generate only a rise of 1.96% in mining exploration investments in the region.

Regarding the impact of social conflicts (SECD) on mining exploration investments, North America has the lowest elasticity. The result implies that a 1% increase in the SECD variable would generate a reduction of 0.05% in mining exploration investments. In contrast, Europe would be the region with the most significant decrease in the level of mining investments generated by an increase in social conflicts. In this region, a 1% increase in the SECD variable would reduce 1% of mining exploration investments. Finally, the population density variable (POPD) would also harm the level of mining investments, with North America and Asia being the regions with the lowest and highest reduction in the level of mining exploration expenditures, respectively.

Fifth, based on the estimated elasticities and through one-tail Wald hypothesis tests, we show that the investment climate (IEF) exhibits, on average, a higher elasticity than the geological potential (GVMP). This result allows us to validate the "alternative view” of mining competitiveness (Johnson, 1990; Tilton, 1992), which establishes that the investment climate is the most relevant factor in explaining the mining competitiveness of a country. Likewise, the

Wald tests reject the hypothesis that the geological potential is the most significant variable to foster mining competitiveness.

Likewise, through a quantile analysis, we show that the geological potential has an insignificant impact in stimulating investments in mining exploration in countries that attract low amounts of expenditures (located in the first five deciles of the distribution of exploration expenditures). In this case, only the investment climate has a significant elastic effect on attracting mining investments to a country. However, we show that the geological potential begins to have an inelastic impact starting at the sixth decile. This result explains why in countries that attract moderate and high levels of mining investment; the geological potential becomes a more relevant factor in attracting higher investments. From the quantile 85% of the distribution of exploration expenses, the geological potential has a more elastic effect on mining investment. Hence, we demonstrate that, regardless of the amount of investment allocated to a country, the investment climate is always an important factor in stimulating the allocation of exploration expenditures in a country, which provides more empirical support to the hypothesis of the "alternative view" of mining competitiveness.

To sum up, the competitiveness of a country to attract mining exploration investment will depend not only on its geological endowment of mineral resources but also on its ability to provide mining companies with a favorable institutional climate that encourages them to invest. Hence, countries with a more stable business environment will be successful in attracting a higher level of mining exploration investment. Countries' mining competitiveness can be negatively affected if the number of mining social conflicts in the territory increases, or if governments do not establish policies that consistently coordinate demographic growth and urban development with the mining activity.

The results we obtain in this research constitute a contribution to support, based on empirical evidence, the design of public policies that promote the competitiveness of a country to attract mining exploration investments based on the management of the four factors analyzed in this paper. The regional analysis developed in this document also identifies that the effects of the determinants of mining competitiveness vary in each region of the world, so it is necessary to design public policies that fit the institutional particularities of that region.

Governments of countries wishing to sustain their economic growth through the development of their domestic mining industry must design strategic mining development sectorial plans that allow the deployment of policies to manage the four factors that determine mining competitiveness identified in this paper. These plans should articulate the effort of different ministries and entities to ensure that the mining policies deployed can be executed in a coordinated manner. This task is not easy because it requires the commitment not only of central government authorities but also of local mining companies and civil society in general. Therefore, these plans must be planned in coordination with related sectors deployed in the long term (10 to 20 years), and frequently reviewed to ensure their technical validity and social legitimacy.

6. Bibliography

African Minerals Development Centre. (2017). *Geological and Mineral Information Systems.* Ethiopia: Economic Commission for Africa.

Andrews, D. W. (1993). Tests for parameter instability and structural change with unknown change point. *Econometrica, 61*(4), 821-856.

Barham, B., & Coomes, O. (2005). Sunk costs, resource mining industry, and development outcomes. In O. Ciccantell, D. Smith, & G. Seidman, *Nature, raw materials, and political* (pp. 159-186). London: Emerald Group Publishing Limited.

Billington, N. (1999). The location of foreign direct investment: an empirical analysis. *Applied Economics, 31*(1), 65-76.

Breusch, T., & Pagan, A. (1980). The Lagrange Multiplier Test and Its Applications to Model Specification in Econometrics. *The Review of Economic Studies, 47*(1), 239–253. Retrieved from www.jstor.org/stable/2297111.

Brown, R., Durbin, J., & Evans, J. (1969). Techniques for Testing the Constancy of Regression Relationships over Time. *Journal of the Royal Statistical Society, 37*(2), 1-15.

Cameron, A. C., & Trivedi, P. (2009). *Microeconomics using Stata.* College Station, TX: Stata Press.

Cameron, C., & Trivedi, P. (1990). Regression Based Tests for Overdispersion in the Poisson Model. *Journal of Econometrics, 46*(3), 347-364.

Cameron, C., & Trivedi, P. (2005). *Microeconometrics. Methods and Applications.* New York: Cambridge University Press.

Cave, D., & Kwai, I. (2019, April 25). Cómo Australia se desencantó de la inmigración. *The New York Times*.

Cheng, L., & Kwan, Y. (2000). What are the determinants of the location of foreign direct investment? The Chinese experience. *Journal of International Economics, 51*(2), 379-400.

CIA. (2014). *The World Factbook.* Washington DC: Central Intelligence Agency. Retrieved from https://www.cia.gov/library/publications/download/download-2014

Collier, P., & Hoeffler, A. (1998). On economic causes of civil war. *Oxford Economic Papers, 50*, 563-573.

Davis, G., & Vásquez Cordano, A. (2013). International Trade in Mining Products. *Journal of Economic Surveys, 27*(1), 74-97.

Diario Olé. (2019, June 30). La lucha por los derechos laborales y políticos en la España del siglo XX: El centenario de la huelga de Las Forjas de Buelna. *Diario Olé*. Retrieved from https://www.eldiario.es/cantabria/desmemoriados/Espana-XX-centenario-Forjas-Buelna_6_914868523.html

Dixit, A., & Pindyck, R. (1994). *Investment under Uncertainty.* New Jersey: Princeton University Press.

Eggert, R. (1992). Exploration. In M. J. Peck, H. H. Landsberg, & J. E. Tilton, *Competitiveness in Metals. The Impact of Public Policy* (pp. 21-67). London: Mining Journal Books.

Estrella, R., Miranda, C., & Sánchez, W. (2015). Master Thesis (Mine Management). *Factores que determinan la inversión en exploración minera*. Lima: GERENS Graduate School.

Euronews. (2018, December 05). Macron renuncia a la subida de los carburantes para calmar las protestas. *Euronews*. Retrieved from https://es.euronews.com/2018/12/05/macron-renuncia-a-la-subida-de-los-carburantes-para-calmar-las-protestas

Eurostat. (2019, September 10). *Eurostat Statistics Explained*. Retrieved from Estadísticas de la población a nivel regional: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Population_statistics_at_regional_level/es&oldid=196176#Densidad_de_poblaci.C3.B3n

Franasovic, Y. (2017). Thesis (Mining Eng.). *Análisis de elementos competitivos que inciden en la inversión en exploración minera de cobre*. Santiago de Chile: Universidad de Chile.

Garside, M. (2019, September 04). *Statista*. Retrieved from Major countries in copper mine production worldwide from 2010 to 2018: https://www.statista.com/statistics/264626/copper-production-by-country/

Gold Hub. (2019, April 4). *Gold Mine Production*. Retrieved from https://www.gold.org/goldhub/data/historical-mine-production

Goldberger, A. (1968). The Interpretation and Estimation of Cobb-Douglas Functions. *Econometrica, 36*(3), 464-472.

Gourieroux, C., Monfort, A., & Trognon, A. (1984). Pseudo Maximum Likelihood Methods: Applications to Poisson Models. *Econometrica, 52*, 701-720.

Grossman, H., & Kim, M. (1995). Swords or Plowshares? A Theory of the Security of Claims to Property. *Journal of Political Economy*, 1275-1288. Retrieved from www.jstor.org/stable/2138711

Gujarati, D., & Porter, D. (2009). *Basic Econometrics* (5 ed.). New York: McGraw-Hill Irwin.

Haberler, G. (1977). Survey of circumstances affecting the location of production and international trade as analyzed in the theoretical literatures. In B. Ohlin, P.-O. Hesselborn, & P. M. Wijkman, *The International Allocation of Economic Activity. Proceedings of a Nobel Symposium held at Stockholm.* London: The MacMillan Press.

Huaroto, C., & Vásquez Cordano, A. (2015). *Los Conflictos Socio-Ambientales y el Valor de las Acciones de las Grandes Empresas Mineras en el Perú: Evaluando la Teoría de las Opciones Reales.* Lima: Osinergmin. Documento de Trabajo No 34, Oficina de Estudios Económicos.

Huber, P. (1965). The behavior of maximum likelihood estimates under nonstandard conditions. *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability. 1*, pp. 221-233. Berkeley: University of California Press.

ICMM. (2012). *Trends in the mining and metals industry. Mining's contribution to sustainable development.* London: International Council on Mining & Metals.

Idean, S., Cullen, S. H., Hammer, J., Case, C., Linebarger, C., Stull, E., & Williams, J. (2012). Social Conflic in Africa: A New Database. *International Interactions, 38*, 503-511. doi:10.1080/03050629.2012.697426

Imai, K., & Weinstein, J. (2000). Measuring the Economic Impact of Civil War. *Working Paper N° 51 - Center for International Development at Harvard University*. Retrieved from http://www.cid.harvard.edu/cidwp/051.pdf

International Monetary Fund. (2019, September 29). *Report for Selected Countries and Subjects.* Retrieved from https://www.imf.org/external/pubs/ft/weo/2019/01/weodata/weorept.aspx?sy=2017&ey=2024&scsm=1&ssd=1&sort=country&ds=.&br=1&pr1.x=113&pr1.y=20&c=193%2C867%2C868%2C836%2C196%2C565%2C853%2C862%2C819%2C813%2C866%2C869%2C826%2C846&s=NGDP_R&grp=0&a=#download

Jara, J. (2008). Working paper. *Factores que determinan el atractivo de un país para las inversiones en exploración: un aporte desde la econometría*. Comisión Chilena del Cobre (COCHILCO) - Dirección de Estudios.

Jara, J. (2017). Determinants of country competitiveness in attracting mining investments: An empirical analysis. *Resources Policy, 52*, 65-71. Retrieved from https://doi.org/10.1016/j.resourpol.2017.01.016

Jara, J., Lagos, G., & Tilton, J. (2008). Using exploration expenditures to assess the climate for mineral investment. *Resources Policy, 33*(4), 129-187. Retrieved from https://doi.org/10.1016/j.resourpol.2008.08.003

Jensen, J. L. (1906). Sur les fonctions convexes et les inégalités entre les valeurs moyennes. *Acta Mathematica, 30*(1), 175-193.

Johnson, C. (1990). Ranking countries for minerals. *Natural Resource Forum, 14*(3), 178-186. doi:10.1111/j.1477-8947.1990.tb00516.x

Kang, S., & Meernik, J. (2005, Febrero). Civil War Destruction and the Prospects for Economic Growth. *The Journal of Politics, 67*(1), 88-109. Retrieved from https://www.jstor.org/stable/10.1111/j.1468-2508.2005.00309.x

Kaufman, D., Robinson, M., & Cruz Vieyra, J. (2019). How Latin America Can Use its Natural Resource Wealth Responsibly. *Americas Quarterly*. Retrieved from https://www.americasquarterly.org/content/how-latin-america-can-use-its-natural-resource-wealth-responsibly

Khindanova, I. (2005). Working Paper. *The location of investment in non-fuel minerals exploration: Intercountry comparisons*. Colorado School of Mines.

Khindanova, I. (2006). Working Paper. *The location of investment in non-fuel minerals exploration: Intercountry comparisons*. Colorado School of Mines.

Khindanova, I. (2007). Working Paper. *The location of investment in non-fuel minerals exploration: Intercountry comparisons*. Colorado School of Mines.

Khindanova, I. (2011). Location factors for non-ferrous exploration expenditures. *Journal of Applied Business and Economics, 12*(1), 38-45.

Khindanova, I. (2015). Exploration funding and the mineral investment climate. *Journal of Finance and Accountancy, 19*(March), 1-12. Retrieved from http://www.aabri.com/OC2015Manuscripts/OC15030.pdf

Leamer, E. E. (1984). *Source of International Comparative Advantage: Theory and Evidence.* Cambridge, MA: MIT Press.

Mancini, L., & Sala, S. (2018). Social impact assessment in the mining sector: Review and comparison of indicators frameworks. *Resources Policy*, 98-111. Retrieved from https://doi.org/10.1016/j.resourpol.2018.02.002

Manning, W. G., & Mullahy, J. (2001). Estimating Log Models: To Transform or Not to Transform? *Journal of Health Economics, 20*(4), 461-494.

McCullagh, P., & Nelder, J. (1989). *Generalized Linear Models.* London: Chapman and Hall.

Melguizo, Á. (2017). If we want more economic growth in Latin America, we need more and better taxes. *World Economic Forum on Latin America*. Retrieved from https://www.weforum.org/agenda/2017/03/if-we-want-more-economic-growth-in-latin-america-we-need-more-and-better-taxes/

Moroney, J. R. (1975). Natural resource endowments and comparative labor costs: A model of comparative advantange. *Journal of Regional Science, 15*(2), 139-150.

Naito, K., Otto, J., & Eggert, R. (1998). Mineral investment risk and opportunities in Asia. *Resources Policy, 24*(2), 77-78.

Ohlin, B. (1933). *Interregional and International Trade.* Cambridge: Harvard University Press.

Otto, J. (1992). Criteria for Assessing Mineral Investment Conditions. In U. Nations, *Minetal Investment Conditions in selected Countries of the Asia-Pacific Region* (pp. 6-34). New York: United Nations Publishing.

Population Pyramid. (2019, September 05). *Population Pyramids of the World from 1950 to 2100*. Retrieved from PopulationPyramid.net: https://www.populationpyramid.net/africa/2017/

Pregibon, D. (1979). PhD Dissertation. *Data analytic methods for generalized linear models*. University of Toronto.

Przeworski, A., & Curvale, C. (2006). *Political Institutions and Economic Development in the Americas: The long run.* New York: Department of Politics. New York University. Retrieved september 09, 2019, from https://as.nyu.edu/content/dam/nyu-as/faculty/documents/salamanca_en.pdf

Ramsey, J. (1969). Tests for Specification Errors in Classical Linear Least Squares Regression Analysis. *Journal of the Royal Statistical Society, B 31*(2), 350-371.

Rodrik, D. (1999, Diciembre). Where Did All the Growth Go? External Shocks, Social Conflict, and Growth Collapses. *Journal of Economic Growth, 4*(4), 385-412. Retrieved from https://www.jstor.org/stable/40216016

Silva, J. S., & Tenreyro, S. (2006). The Log of Gravity. *Review of Economics and Statistics, 88*(4), 641-658.

SNL. (2014). *Corporate Exploration Strategies.* Canada: SNL.

StataCorp. (2017). *Stata Statistical Software: Release 15*. College Station, Texas: StataCorp LP.

Stedman, A., & Green, K. P. (2018). *Annual Survey of Mining Companies.* Canada: Fraser Institute.

The Heritage Foundation. (2014). *The Index of Economic Freedom.* New York: The Heritage Foundation and Wall Street Journal.

The Heritage Foundation. (2018, December 25). *Index of Economic Freedom - Country Rankings.* Retrieved from https://www.heritage.org/index/ranking

The Heritage Foundation. (2019). Regional Developments in Economic Freedom (Chapter 5). In *Index of Economic Freedom.* Retrieved from https://www.heritage.org/index/book/chapter-5

Tilton, J. (1983). *Comparative Advantage in Mining.* Laxenburg: International Institute for Applied Systems Analysis.

Tilton, J. (1992). Mineral endowment, public policy and competitiveness. *Resources Policy, 18*(4), 237-249. Retrieved from https://doi.org/10.1016/0301-4207(92)90008-W

Tilton, J., & Guzman, J. I. (2016). *Mineral Economics and Policy.* New York: Routledge.

Vanek, J. (1963). *The Natural Resource Content of United States Foreign Trade, 1870-1955.* Cambridge, MA: MIT press.

Vivoda, V. (2017). Determinants of Foreign Direct Investment in the Mining Industry. In T. O'Callaghan, & G. Graetz, *Mining in the Asia-Pacific. The Political Economy of the Asia Pacific* (pp. 19-33). Berlin: Springer International Publishing.

White, H. (1980). A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica, 48*(4), 817-838.

Wooldridge, J. (2002). *Introductory Econometrics. A Modern Approach* (5 ed.). Mason, OH: South-Western, Cengage Learning.

Wooldridge, J. (2010). *Econometric Analysis of Cross Section and Panel Data* (2 ed.). Cambridge, MA: MIT Press.

World Bank. (2014). *World Development Indicators.* Washington DC: World Bank.

GĚRENS ESCUELA DE POSTGRADO

gerens.pe

informes@gerens.pe

(511) 702-9800

Av. Primavera 1050, Surco, Lima - Perú