Mineral Economics (2020) 33:231–243
https://doi.org/10.1007/s13563-020-00230-7

ORIGINAL PAPER

Attracting mining investments: the relationship between natural endowments and public policies

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Received: 11 February 2020 / Accepted: 2 June 2020 / Published online: 15 June 2020

Abstract

Mining jurisdictions avid to attract international investments to find and exploit their mineral deposits contend for international capitals. This led to policymakers, analysts, and companies to think about the factors affecting the competitiveness of mining districts. The traditional paradigm states that the capacity of a country or jurisdiction to attract investments and develop its local industry is a function exclusively of the quantity and quality of the ore deposits within its territory. On the other hand, the alternative view suggests that the previous conception is incomplete, because companies not only look for a good geologic potential but also for a favorable investment climate (Tilton 1992). Through cross-country econometric models covering the years 1996 to 2014, this work supports the alternative paradigm of mining competitiveness and tries to contribute to a better understanding of the relationship between the geological potential and the investment climate when determining the attraction of mining investments. The study concludes that, in order to develop a local mining industry, a country should have a wealthy natural endowment, but also it must offer a good investment climate. In addition, it shows that both variables are related through a multiplicative effect, but once public policies and other contextual variables reach certain reasonable levels (the "investment climate threshold"), jurisdictions compete almost exclusively based on its natural endowment. These results have significant implications for the implementation of public policies, especially in periods when mining contribution to social welfare is under scrutiny.

Keywords Competitiveness · Geologic potential · Investment climate · Cross-country models · Exploration expenditures · Index of economic freedom

Introduction

The years that Professor John Tilton spent in Chile left a profound mark in our country, especially in the Department of Mining Engineering at the Pontificia Universidad Católica de Chile (DIM-UC). In 1999, Professor Gustavo Lagos, at that time director of the Mining Center UC, invited John (who was recently starting the retirement process at Colorado School of Mines) to come to Chile and assist him in creating an academic program in mineral economics. Despite the relevance of the mining industry, no academic programs or research groups dealing with these issues were active in our country at that time. The program would be funded by the state and the local industry. And so it was.

As a result, Professor Tilton was made a full professor at the Pontificia Universidad Católica de Chile (UC), he spent one semester per year in Chile for more than 15 years, and a Master of Science program in mineral economics was created. During that period, John regularly gave a course on mineral economics, guided and co-guided over two dozen master and doctoral students, and contributed editorially and with articles to the publication of 8 books in Spanish on a series on mineral economics (Foro en Economía de Minerales), and with papers in peer reviewed journals. Professor Tilton still participates, now from the USA, in co-guiding masters and Ph.D. students, and he is active publishing academic articles jointly with professors at UC and with his former students, now renowned experts in the mineral economics.

This experiment was not only highly successful but also turned out to be quite invigorating, contributing with new ideas and research hypothesis for different topics in the field.

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An advisory committee to the program was created with the participation of other world renowned mineral economists, namely Professor Marian Radetzki, formerly at Lulea University in Sweden, Dr. David Humphreys from Rio Tinto in the UK, and Professor Roderick Eggert from the Colorado School of Mines in the USA. The Chilean members of this board were Professor Marcos Lima, a former Codelco CEO, and Professor Gustavo Lagos. This group would meet periodically, generating the most exciting discussions and issuing relevant research questions for the students. Following the best academic traditions, John would arrive to lunch and coffee time, always with a small piece of paper containing a list of topics to be discussed. And he made sure that everyone else understood the fine arguments that he was putting forward, which were not always shared by all the participants.

Professor Tilton's intellectual contribution to the mining industry in Chile is manifested. Though, anybody who had the pleasure to meet him knows that his most significant legacy remains in his humanity: extremely kind, especially with students and personnel; always open to listen others and to share his wisdom and knowledge; constantly worried about the person and their relatives; and with a genuine concern about the underprivileged of our societies. In this regard, his wife Liz have played a crucial role in organizing and supporting John's long visits to Chile, but more in creating a warm and kind atmosphere to those of us who had the pleasure to share with them in Chile.

A recurrent topic in our conversations with John during his years in Chile was the pathways that different mineral rich countries experienced in terms of their mining sectors. John always highlighted the case of Chile and how its good public policies beneficiated the country and the fact that (almost) nobody questioned these policies. Finally, these discussions led to the publication of a couple of scientific articles: the first one dealing with the problem to measure countries' long-term mining competitiveness (Jara et al. 2008) and the second one trying to model, through cross-country regressions, the relationship between natural endowments and public policies in assessing the attraction of mining investments (Jara 2017).

The aim of this paper, as a tribute to John Tilton and a way to maintain his legacy in such a difficult time for our country, is to give additional support to one of his several key contributions to the field of mineral economics: to strongly remark and communicate the essential role of public policies for having local mining sectors that could contribute to the sustainable development of countries, especially in developing economies.

The ownership structures of the extractive industries followed divergent patterns in the last decades. In the oil and gas sector, state-owned companies took the control of a major share in global reserves and production in many countries. At the same time, most countries that are naturally rich in metals, uranium, and coal deposits, privatized their mining industries (Jara et al. 2008). This led to a prominent participation of private multinational enterprises in mining worldwide. As a result, jurisdictions avid to attract investments to find and exploit their mineral deposits contend for international capitals. This situation led to policymakers, analysts, and companies to think about the factors affecting the competitiveness of mining districts.

Usually competitiveness is measured by the market share captured by a company, an economic sector or a country, which could be increased through providing cheaper or better products to the costumers. However, the mining industry produce mineral commodities that are (in general terms) homogeneous and standardized. Thus, the only way for companies or countries to raise their mining competitiveness is reducing their costs (Tilton 1992).

Mining costs strongly depend on a series of variables related to the natural characteristics of the ore bodies and the methods used to exploit them. Some are geologic in nature as the size of the deposit, its depth of emplacement, and the distribution of its grades. Others are technical like the mining method to extract the ore or the metallurgical process to obtain the final product. All these factors deal with the main concerns of mining professionals and frequently can determine the economic viability of a mining operation without any other consideration. This partial view (historically, the company space of action; currently, the operation's one) led to the traditional paradigm of competitiveness in mining: the capacity of a country or jurisdiction to attract investments and develop a local mining industry is a function exclusively of the quantity and quality of the deposits within its territory. Without them, there is almost nothing that companies or governments can do to improve their position.

This conceptual model is based on the literature on international trade and particularly on the factor endowment theory (Heckscher 1949), which states that countries tend to produce and export the goods that can be cheap to produce in their territories. Thus, China and India should export goods that are labor intensive, Australia, those that are reliant on natural resources, and the UK, the products or services dependent on financial sources. Consequently, mineral commodities should be produced in and exported by countries on which deposits are richer and mining costs smaller.

However, the evidence suggests that the natural endowment of a country cannot completely explain its capacity to attract mining investments (Tilton 1983; Jara 2017). In the 1960s and 1970s, several resource-rich countries implemented actions to increase taxes and nationalize companies and other policies in order to increase the government's share of the mining rents. The result in most cases was stagnation, or even reduction, in their global share of mineral commodities production, despite their enormous, high-quality mineral resources (Tilton 1992).

Therefore, during the 1980s and first half of the 1990s, an alternative paradigm was built to assess the variables that influence the attraction of mining investments. It stated that the previous conception of mining competitiveness is not incorrect but incomplete, because companies not only look for a good geologic potential but also for a favorable investment climate (Tilton 1992). Among the factors frequently included in a good investment climate were the following: availability of infrastructure; skilled local workforce and advanced human capital; sociopolitical stability; clear, long-term regulations and institutions; adequate tax regime; and specific regulatory framework to enhance mining activities (Johnson 1990; Fraser Institute, several years).

There have been more than 30 years since the inception of this alternative paradigm, a concept that currently has a broad acceptance within the industry and most governments worldwide. However, only a couple of scientific works (Khindanova 2005, 2006, 2007, 2011[1]; Jara 2017) have tried to validate it with empirical data. In her works, Khindanova (2005, 2006, 2007) explained the country allocation of nonferrous exploration budgets[2] in 2002 (MEG 2003) through different variables representing the geological potential and the investment climate of the jurisdictions included in her datasets. Also, Jara (2017) tested both mining attractiveness paradigms against empirical information for the year 2014. These studies have relevant shortcomings, despite their substantial contribution, the most relevant of which is their restricted temporal representation (only 1-year datasets for the analysis of an industry characterized by its long-term perspective).

The purpose of this work is to provide empirical evidence to analyze the attraction of mining investments by countries in a wider temporal timeframe, by extending the work of Jara (2017) to the period 1996 to 2014. Consequently, the article is structured as follows: previous studies are reviewed in the "Previous works' review" section; The "Data description" section presents the data used in the study; the models, criteria selection and results are shown in the "Model specifications, criteria selection, and results" section; and finally, The "Discussion and recommendations" section discusses the main outcomes of the research and provides some recommendations for future works.

Previous works' review

Khindanova's articles (Khindanova 2005, 2006, 2007, 2011) are the only econometric studies that try to assess the influence of geological potential and investment climate on the geographical distribution of exploration budgets. All her models incorporate the natural logarithm of exploration budgets by country as the dependent variable. The first work (Khindanova 2005) starts with a search for the best proxies of country's geological potential and investment climate (independent variables). It finally concludes that the country's land area is a good choice for the former and the index of economic freedom (Heritage Foundation 2014) or the governance indicator (World Bank 2019) is the best ones for the latter.

In her first cross-country models, the author uses an additive functional form:

$$\boldsymbol{lnExpl_i} = c + b_1 x_{1,i} + b_2 x_{2,i} + \varepsilon_i \quad (1)$$

where $\boldsymbol{lnExpl_i}$ is the natural logarithm of the exploration budget in country 'i'; $x_{1,i}$ and $x_{2,i}$ are the proxies for the geological potential and the investment climate for the same country, respectively; and $\varepsilon_i \sim N(0, \sigma^2)$ is the error term.

In Khindanova (2006), new independent variables are used to explain the allocation of exploration budgets. To account for the size of the economy of each country, GDP and population series are included, in addition to an interaction term between the political (investment climate) and geological potentials ($x_1 x_2$). In this way, when the investment climate is particularly low a high geological potential should have minor impact on the country competitiveness.

An important conclusion of this work is that the population nor the GDP variables are statistically significant, which implies that the availability of capitals from the local economy is not relevant when the natural endowment is scarce or the investment climate is poor. However, the author could not improve the model's performance through the inclusion of these additional independent variables (adj. $R^2 \sim 0.45$). Nevertheless, a noticeable outcome of the study is that the interaction term $x_1 x_2$ was statistically significant, which implied that both variables (geological potential and investment climate) are relevant to measure mining attractiveness. This result is in agreement with the common sense. Though, it should be noted that the purely additive model is questionable from an economic perspective, particularly for extreme values in the independent variables. For example, in this model, a very small country (in terms of land area) with an excellent climate for investment could capture a high percentage of the global exploration budgets, although the probability to find a series of world class deposits is extremely low. Analogously, a country with the worst political potential (for example, in constant civil war or under an authoritarian, corrupt government) but having a huge geological potential could be highly competitive, even though mining activities could not be carried on its territory.[3]

[1] These documents are different versions of the same research.

[2] The country's share on exploration budgets/expenditures could be good proxy of mining competitiveness (Jara et al. 2008).

[3] There have been several examples of this situation during the last decades; civil war in the former Yugoslavia (1991–2001), Chad (2005–2010), Afghanistan (1978-) or Sudan (2013-); authoritarian and corrupt governments in some African and Latin American countries.

Khindanova uses the natural logarithm transformation of the dependent variable and the independent ones that have high dispersion (population and GDP series) but not for the proxies of geological potential and investment climate. This implies that the variables in her models do not have a common scale of measure. This situation arises because the objective was to analyze the geographical allocation of exploration budgets and not the countries mining competitiveness.

Jara (2017) uses a common scale between the independent and dependent variables, trying to evaluate the attraction of mining investments. The study incorporates the advances made by Khindanova on the identification of proxies for geological potential (land area of the countries) and for investment climate (index of economic freedom), and the use of an interaction term between both exogenous variables. Additionally, the author does not impose a functional form to the mining competitiveness model and uses the Taylor expansion series (up to the second order) to find the best alternative for this purpose (details of the methodology are given in the "Model specifications, criteria selection, and results" section).

From the 21 cross-country models in Jara (2017), those that include the interaction term yield better results (adj. R^2~0.66 to 0.78). Unfortunately, the best regression presents negative values for the geological potential proxy, contradicting the economic rationale of the model. The author explains this result suggesting the presence of a structural break in the behavior of mining companies when faced to contrasting investment environments. When there are two jurisdictions having similar geological potential, mining companies prefer to invest on the one that has a better investment climate. However, when countries reach a certain threshold of investment climate, companies are indifferent to this variable and take their decision almost exclusively based on the probability to find a good deposit. Therefore, below this "investment climate threshold", the interaction term between both variables is valid, but above it, only the proxy for the geological potential defines the mining competitiveness of those countries.

The results given by this "structural break model" are excellent, with all the estimated parameters showing a high statistical significance, signs concordant to the economic rationale and reaching an adj. R^2 of 0.81. In addition, the estimated constant term of the model is close to zero, which agrees with the economic theory (null geological potential and/or null investment climate must imply zero mining competitiveness). The outcome of this study represents clear evidence that supports the alternative paradigm of mining competitiveness. Countries that want to attract foreign and local funds to develop their mining industries must offer adequate conditions for this to happen. Nevertheless, these results could be specific for the period covered by the study (2014) and may not be extrapolated on time.

The present article contributes by extending the methodology proposed by Jara (2017) to the period between 1996 and 2014, testing whether its conclusions are the result of a long-standing behavior of mining companies in a globalized world or they are specific for the year analyzed by him.

Data description

The sample is composed by a series of cross-country datasets for the period 1996 to 2014. It includes the following variables for each year: the percentage of exploration budgets per country (country budget over global budget of the year) as a mining competitiveness indicator; the index of economic freedom of each country as the investment climate proxy; and the percentage of land area per country (country's land area over the land area of all the countries considered that year) as the proxy for the geological potential.

Information on total exploration budgets by country was obtained from the "Corporate Exploration Strategies" report published by the Metals Economic Group and SNL (MEG/SNL, several years). These series were kindly provided by Minera Los Pelambres and Antofagasta Minerals, as part of a contract research on the competitiveness of the Chilean mining industry and its future developments. This data includes exploration budgets for nonferrous metals, diamonds, and radioactive minerals (uranium in particular) for each year and are based on a global survey.[4]

Following the recommendations of Khindanova (2007, 2011), this work uses land areas as proxies of the geological potential. Data on the land extension of the territories for each country were obtained from the "World Factbook 2014" website of the Central Intelligence Agency of the USA (CIA 2015).

Finally, the index of economic freedom, published every year since 1995 by the Heritage Foundation and the Wall Street Journal, was used as a measure of the investment climate. This index reflects the economic conditions prevailing in each country, and it is based on 10 indicators for specific areas of the business environment: business freedom, trade freedom, fiscal freedom, government spending, monetary freedom, investment freedom, financial freedom, property rights, freedom from corruption, and labor freedom. Specific indicators vary between 0 and 100, with higher values reflecting better economic conditions. Detailed information on the methodology is available online (Heritage Foundation 2014).

Summary statistics for each dataset and per year are presented in Table 1. The number of observations is obtained after excluding those countries that do not have an index of economic freedom or do not captured enough exploration budgets in that particular year. As can be seen from the statistics, the datasets conform a nonbalanced panel data. Exploration budgets and land areas are highly positive skewed

[4] The yearly dataset has slightly changed over time; however, these modifications have no impact on the conclusions of the study.

Table 1 Summary statistics of the datasets used in econometric modeling

	N°Obs	Percentage of exploration budgets by country					Normalized index of economic freedom by country					Percentage of land area by country				
Year	n	Mean	Median	St.Dev.	$P_{5\%}$	$P_{95\%}$	Mean	Median	St.Dev.	$P_{5\%}$	$P_{95\%}$	Mean	Median	St.Dev.	$P_{5\%}$	$P_{95\%}$
1996	48	2.08%	0.28%	4.44%	0.02%	10.47%	0.5705	0.5912	0.1145	0.3908	0.7445	2.08%	0.71%	3.64%	0.07%	10.19%
1997	58	1.72%	0.31%	3.53%	0.01%	7.55%	0.5682	0.5843	0.1139	0.3808	0.7551	1.72%	0.57%	3.09%	0.07%	9.26%
1998	59	1.69%	0.30%	3.52%	0.02%	7.75%	0.5688	0.5907	0.1172	0.3806	0.7497	1.69%	0.57%	2.98%	0.07%	9.01%
1999	54	1.85%	0.41%	3.90%	0.02%	9.12%	0.5840	0.6123	0.1161	0.3621	0.7494	1.85%	0.73%	3.18%	0.10%	9.34%
2000	58	1.72%	0.41%	3.77%	0.05%	7.60%	0.5843	0.5956	0.1120	0.3668	0.7613	1.72%	0.55%	3.03%	0.10%	9.10%
2001	53	1.89%	0.37%	4.05%	0.03%	7.94%	0.6011	0.6062	0.1047	0.4213	0.7807	1.89%	0.59%	3.40%	0.10%	9.84%
2002	53	1.89%	0.31%	4.16%	0.01%	7.39%	0.6049	0.6017	0.1017	0.4211	0.7800	1.89%	0.59%	3.40%	0.10%	9.84%
2003	55	1.82%	0.25%	4.28%	0.01%	7.09%	0.6027	0.5896	0.0987	0.4290	0.7764	1.82%	0.58%	3.27%	0.09%	9.42%
2004	57	1.75%	0.32%	3.91%	0.03%	6.76%	0.5985	0.5917	0.0979	0.4343	0.7810	1.75%	0.58%	3.19%	0.09%	9.32%
2005	60	1.67%	0.43%	3.55%	0.01%	6.00%	0.5933	0.5748	0.0929	0.4794	0.7904	1.67%	0.51%	3.12%	0.07%	9.26%
2006	62	1.61%	0.40%	3.40%	0.01%	6.69%	0.5967	0.5883	0.0955	0.4534	0.7980	1.61%	0.51%	3.03%	0.07%	9.08%
2007	64	1.56%	0.25%	3.66%	0.01%	6.23%	0.5969	0.5775	0.0960	0.4691	0.8068	1.56%	0.49%	2.97%	0.05%	8.94%
2008	65	1.54%	0.29%	3.55%	0.01%	6.52%	0.5983	0.5976	0.0982	0.4718	0.8062	1.54%	0.49%	2.96%	0.05%	9.01%
2009	118	0.85%	0.12%	2.23%	0.01%	5.03%	0.5899	0.5820	0.0979	0.4528	0.7841	0.85%	0.26%	1.94%	0.02%	3.21%
2010	119	0.84%	0.13%	2.37%	0.00%	3.87%	0.5887	0.5890	0.1084	0.4275	0.7728	0.84%	0.25%	1.93%	0.02%	3.03%
2011	115	0.87%	0.14%	2.34%	0.01%	4.07%	0.5885	0.5950	0.1073	0.4168	0.7537	0.87%	0.26%	1.98%	0.02%	3.78%
2012	124	0.81%	0.11%	2.13%	0.00%	3.52%	0.5852	0.5755	0.1054	0.4494	0.7681	0.81%	0.24%	1.87%	0.02%	2.57%
2013	123	0.81%	0.14%	2.08%	0.01%	4.75%	0.5923	0.5960	0.1010	0.4365	0.7561	0.81%	0.25%	1.91%	0.02%	2.64%
2014	122	0.82%	0.17%	2.08%	0.00%	5.26%	0.5960	0.5916	0.0965	0.4452	0.7542	0.82%	0.25%	1.92%	0.02%	2.66%

every year, and few countries represent a big share of totals. Meanwhile, the index of economics is rather homogeneously distributed around the mean. It is important to notice the increase in observations per year since 2009, almost doubling those of the previous periods.

Model specifications, criteria selection, and results

One of the shortcomings to apply the logarithmic transformation to some variables in a regression model are that there is not a common scale among the estimated parameters and that some of them could present negative values that are contradictory with the economic rationale in the model specification. To overcome this problem, Jara (2017) used normalized values of the variables. Thus, the competitiveness indicator is calculated as the percentage of global exploration expenditures allocated to each country (***PExpl**$_i$*). The index of economic freedom is a normalized variable that varies between 0 and 100, so to have it in the same range of the other variables, it is necessary to divide it by 100 (***NIEF**$_i$*). Finally, for the geological potential proxy, the procedure is similar to that used for the exploration budgets: the land areas of the countries that have an exploration budget and an index of economic freedom reported in a particular year are totalized (land area here refers to country's dry surface, and it does not take into account undersea territories). Then, a percentage of this total land area is assigned to each country, which is calculated as the country's land area over total land area of that year (***PLand**$_i$*). It is important to notice that in spite of the fact that the land area of any particular country is fixed, this indicator of geological potential varies over time since the total land area change when countries are included/excluded of the sample each year (the number of countries having exploration budgets and a reported economic freedom rating is different each year).

Once the variables are determined, it is necessary to define the functional form of the model. According to the alternative paradigm of mining competitiveness, this could be explained by two factors: the geological potential and the investment climate of the jurisdiction; however, this hypothesis does not state the way in which both variables interact, leading to the following expression (Eq. 2):

$$\boldsymbol{PExpl_i} = \boldsymbol{f}(\boldsymbol{PLand_i}, \boldsymbol{NIEF_i}) + \varepsilon_i \tag{2}$$

Since f is an unknown function, it could be assessed using the Taylor expansion series (Gómez et al. 2007; Peterman et al. 2007). Consequently, if $f : \Re^2 \Re.$, then the second order Taylor expansion series is obtained by Eq. 3:

$$\boldsymbol{f}(\boldsymbol{x}) = \boldsymbol{f}(\boldsymbol{x_0}) + \nabla \boldsymbol{f}(\boldsymbol{x_0})^T (\boldsymbol{x} - \boldsymbol{x_0}) + \frac{1}{2}(\boldsymbol{x} - \boldsymbol{x_0})^T \boldsymbol{Hf}(\boldsymbol{x_0})(\boldsymbol{x} - \boldsymbol{x_0}) + \boldsymbol{R}(\boldsymbol{x}) \tag{3}$$

where $\boldsymbol{x} = (\boldsymbol{PLand_i}, \boldsymbol{NIEF_i})$ and $\boldsymbol{x_0} = (\boldsymbol{PLand_0}, \boldsymbol{NIEF_0})$ is a vector for an "initial country". In the particular case of this study, Eq. 3 can be rewritten as:

$$\begin{aligned} \boldsymbol{PExpl_i} &= \boldsymbol{f}\ (\boldsymbol{PLand_i}, \boldsymbol{NIEF_i}) + \varepsilon_i \boldsymbol{PExpl_i} \\ &= \boldsymbol{\beta_0} + \boldsymbol{\beta_1 PLand_i} + \boldsymbol{\beta_2 PLand_i^2} + \boldsymbol{\beta_3 NIEF_i} \\ &\quad + \boldsymbol{\beta_4 NIEF_i^2} + \boldsymbol{\beta_5 PLand_i NIEF_i} + \varepsilon_i \end{aligned} \tag{4}$$

where $\boldsymbol{\beta_i}$ are the parameters to be estimated. In this equation, the term $\boldsymbol{\varepsilon_i}$ replaces the residual term of the Taylor expansion $\boldsymbol{R}(\boldsymbol{x})$ in Eq. (4). Taylor expansions are developed here to its second order, since there is no theoretical basis to believe that relations of higher level are necessary. In addition, it was found that several third-order terms do not provide more information or better results. Therefore, Eq. (4) is the general specification of the model for country's mining competitiveness.

Finally, the search of the functional form starts with the simplest models, which incorporates only one independent variable and two parameters to be estimated: $\boldsymbol{\beta_0}$ as the constant of the model and $\boldsymbol{\beta_i}$ ($i = 1, 2, \ldots, 5$) as the parameter for the independent variable. The other four parameters $\boldsymbol{\beta_j}$ are set as zero. This gives five models 'A'. Then, the process continues but including two independent variables and three parameters: $\boldsymbol{\beta_0}$, $\boldsymbol{\beta_i}$ ($i = 1, 2, \ldots, 5$) and $\boldsymbol{\beta_j}$ ($j = 1, 2, \ldots, 5; j \neq i$) and producing 10 models 'B'. The procedure is repeated until the only model that incorporates five independent variables and six parameters, the model 'E' (models 'C' and 'D' include three and four independent variables respectively), is obtained. As a result, 31 models could be generated for each year considered in the study.

After obtaining the regressions, three criteria are applied to choose the best model of mining competitiveness. The first one is based on the fit of the models and measured by their adj. R^2. The second looks at the statistical significance of the estimated parameters for the independent variables (95% confidence level). Finally, all the estimated parameters are either zero or positive (the economic assumption is that a major geological potential and/or investment climate should lead to higher mining competitiveness). These criteria are expressed in the tables summarizing the results as follow: the adj. R^2 is tabulated for each year and for each model, remarking in bold those with higher values, and the statistical significance and the sign criteria are expressed as a background palette of colors accordingly to Table 2.

Additionally, the models are also ranked according to their out-of-sample predictive power. To do so, the dataset of 2014 is used to test the models from 1996 to 2013, and their predictive power is measured by the mean squared errors (MSE) between the estimated and the actual results multiplied by 1000. Then, the best models for a particular year are those that present lower mean squared errors.

Models 'A' and 'B'

Table 3 shows the adjusted R^2 values obtained for models 'A' and 'B', together with the background colors of the criteria selection, for each year of the study period. The models with the best fit for each group of models are marked with bold font. In Table 4 the structure of those models is presented. In addition, the out-of-sample predictive power of the same models is presented in Table 5.

For each one of the models 'A', the parameters estimated are statistically significant and show the expected sign, suggesting a correct selection of the variables included in the general specification. However, the performance of the models is mediocre, except for A1 in the last years (adj. $R^2 > 0.4$) and model A5 (the interaction term model) which yields the best fit within the group during the whole study period (Tables 3 and 4). The same results are obtained when analyzing the predictive power of these models: A5 outperform the other models by far, seconded by model A1 (Table 5). It is important to notice that (i) the investment climate by itself is not able to explain more than 20% of the country allocation of exploration budgets and more than double in terms of MSE to the best one-variable model, and (ii) the second order variables (except the interaction term) do not substantially contribute to explain the attraction of mining investments.

Regarding models 'B', it is observed that some of them (B1, B4, B7, and B8) do not comply with at least one of the criteria selection. Particularly, model B8 does not fulfill any of the rules, being the only one that does not include the geological potential in any of its functional forms (Tables 3 and 4). This reinforces the outcome observed in models 'A': the geological potential variable is essential to assess mining competitiveness. In this group, the model showing best fit every single year is B4 (in 1996, B7 presents a slightly better adj. R^2 but in the third significant figure); however, it does not fulfill the

Table 2 Criteria used to choose the best models

(white)	Both criteria are correct (statistical significance and signs of parameters)
(light grey)	Sign criterion correct and significance criterion incorrect
(hatched)	Sign criterion incorrect and significance criterion correct
(dark grey)	Both criteria are incorrect

Table 3 Adjusted $R2$ and criteria selection for models 'A' and 'B'

Year	A1	A2	A3	A4	A5	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
1996	0.2383	0.0815	0.1753	0.2069	**0.3900**	0.4622	0.3716	0.3948	0.6825	0.2469	0.2776	**0.6835**	0.2337	0.4664	0.4811
1997	0.2611	0.0967	0.1531	0.1836	**0.4208**	0.4758	0.3911	0.4148	**0.6991**	0.2473	0.2773	0.675	0.2181	0.4956	0.5114
1998	0.2462	0.0946	0.1341	0.1609	**0.3799**	0.4256	0.3517	0.3737	**0.6676**	0.2163	0.2432	0.644	0.1995	0.4411	0.4567
1999	0.2289	0.0804	0.1547	0.1917	**0.3596**	0.4277	0.3542	0.3855	**0.7254**	0.2201	0.2567	0.6564	0.2393	0.4393	0.4634
2000	0.2797	0.1122	0.1495	0.1842	**0.4325**	0.4707	0.396	0.4224	**0.7604**	0.2482	0.2814	0.6844	0.2296	0.4993	0.5179
2001	0.2713	0.1032	0.1490	0.1708	**0.4325**	0.4872	0.4014	0.4170	**0.7091**	0.2552	0.2748	0.6686	0.1849	0.5103	0.5199
2002	0.3320	0.1617	0.1485	0.1711	**0.5053**	0.483	0.4631	0.4770	**0.7366**	0.3183	0.3362	0.6693	0.1892	0.5786	0.5865
2003	0.3134	0.1502	0.1616	0.1799	**0.4748**	0.4521	0.4401	0.4520	**0.7382**	0.3091	0.3239	0.6463	0.191	0.5488	0.5558
2004	0.3934	0.2175	0.1657	0.1867	**0.5498**	0.5054	0.5099	0.5229	**0.7713**	0.3663	0.3832	0.6945	0.2036	0.6137	0.6211
2005	0.4479	0.2674	0.1722	0.1907	**0.6036**	0.5392	0.5487	0.5576	**0.7674**	0.4144	0.4264	0.7024	0.2022	0.6507	0.6548
2006	0.4586	0.276	0.1596	0.1794	**0.6081**	0.5487	0.5502	0.5587	**0.7507**	0.4069	0.4200	0.7039	0.1924	0.6479	0.6512
2007	0.4437	0.2731	0.1600	0.1854	**0.6123**	0.5202	0.5473	0.5592	**0.7819**	0.4118	0.4291	0.713	0.2162	0.6582	0.6633
2008	0.4277	0.2461	0.1947	0.2334	**0.6187**	0.5348	0.5605	0.5804	**0.7997**	0.4234	0.4505	0.739	0.2948	0.6800	0.6896
2009	0.4980	0.3167	0.0962	0.1248	**0.6484**	0.5606	0.5636	0.5773	**0.7541**	0.3945	0.4142	0.7279	0.1831	0.6747	0.6805
2010	0.4341	0.2503	0.0848	0.1124	**0.6154**	0.5378	0.5027	0.5202	**0.8016**	0.3255	0.3474	0.7463	0.1647	0.6464	0.6549
2011	0.4337	0.2475	0.1010	0.1352	**0.6207**	0.5435	0.5127	0.5340	**0.8253**	0.3358	0.3632	0.7616	0.2130	0.6574	0.6682
2012	0.4447	0.2522	0.1037	0.1284	**0.6237**	0.5565	0.5238	0.5388	**0.8157**	0.3428	0.3621	0.7620	0.1741	0.6622	0.6701
2013	0.5007	0.3065	0.0812	0.1059	**0.6514**	0.5925	0.5690	0.5834	**0.7757**	0.3780	0.3972	0.7488	0.1868	0.6825	0.6900
2014	0.5209	0.3247	0.0802	0.1033	**0.6610**	0.6077	0.5865	0.6019	**0.7676**	0.3951	0.4125	0.7508	0.1931	0.6919	0.6983

sign requirement in any year. Again, the analysis of the predictive power reinforces these results (Table 5). Models B4 and B7 show the lowest MSE of the group. Additionally, it is important to remark the uniformity of the results obtained through the whole study period, which allows presuming a rather stable market behavior in the long run.

Finally, it is interesting to compare three specific models: A1 (the "traditional paradigm model"), A5 (the "interaction model"), and B2 (the "additive effect model"). Even though all of them comply with the criteria selection every year, the "interaction model" outperforms the other two in each period in terms of good of fitness (Tables 3 and 4) and in predictive power (Table 5). This result extends that was observed by Jara (2017) exclusively for the year 2014. Moreover, the four models with higher fit during the whole study period have a common characteristic: all of them have the interaction term ***PLand*NIEF*** incorporated into their functional form.

Models with three or more independent variables: models 'C', 'D', and 'E'

As the best results in models 'A' and 'B' are those including the interaction term ***PLand*NIEF***, the next step is to run the models with three or more variables that incorporates that term (models 'C' with three, models 'D' with four, and model 'E' with five independent variables). The adj. R^2 and criteria selection for these regressions are presented in Tables 6 and 7,

Table 4 Structure of models 'A' and 'B'

	A1	A2	A3	A4	A5	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
β0	β0	β0	β0	β0	β0	β0	β0	β0	β0	β0	β0	β0	β0	β0	β0
PLand	β1					β1	β1	β1	β1						
PLand^2		β2				β2				β2	β2	β2			
NIEF			β3				β3			β3			β3	β3	
NIEF^2				β4				β4			β4		β4		β4
PLand x NIEF					β5				β5			β5		β5	β5

Table 5 Predictive power of models 'A' and 'B' (MSE × 1000)

Year	A1	A2	A3	A4	A5	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
1996	0.2376	0.4132	0.7856	0.8222	**0.1552**	0.2006	0.3538	0.3878	0.1611	0.5809	0.6183	**0.1582**	0.8735	0.2415	0.2677
1997	0.2293	0.3688	0.5873	0.6001	**0.1528**	0.1774	0.2706	0.2855	0.1415	0.4325	0.4472	**0.1265**	0.6166	0.1902	0.2030
1998	0.2282	0.3631	0.5590	0.5634	**0.1562**	0.1730	0.2518	0.2599	0.1687	0.4059	0.4121	**0.1320**	0.5713	0.1824	0.1910
1999	0.2320	0.3841	0.5877	0.6044	**0.1587**	0.1816	0.2664	0.2884	0.2405	0.4324	0.4514	**0.1432**	0.6391	0.1975	0.2187
2000	0.2166	0.3531	0.5545	0.5676	**0.1475**	0.1856	0.2396	0.2559	0.1794	0.3911	0.4064	**0.1353**	0.5853	0.1719	0.1864
2001	0.2264	0.3792	0.5703	0.5632	**0.1502**	0.1917	0.2651	0.2662	0.1320	0.4170	0.4136	**0.1239**	0.5234	0.1899	0.1922
2002	0.2135	0.3525	0.5736	0.5660	**0.1450**	0.1929	0.2646	0.2637	0.1176	0.4044	0.3993	**0.1258**	0.5182	0.1887	0.1892
2003	0.2097	0.3431	0.5994	0.5864	**0.1446**	0.1960	0.2775	0.2724	0.1424	0.4259	0.4151	**0.1365**	0.5304	0.2021	0.1998
2004	0.2071	0.3278	0.5750	0.5631	**0.1444**	0.1873	0.2451	0.2405	0.1258	0.3837	0.3748	**0.1250**	0.5062	0.1766	0.1744
2005	0.2067	0.3194	0.5662	0.5474	**0.1442**	0.1777	0.2280	0.2181	**0.1046**	0.3705	0.3541	0.1123	0.4816	0.1585	0.1530
2006	0.2064	0.3161	0.5197	0.5028	**0.1444**	0.1755	0.2089	0.2000	**0.1026**	0.3356	0.3220	0.1091	0.4437	0.1473	0.1423
2007	0.2049	0.3070	0.5288	0.5146	**0.1456**	0.1839	0.2226	0.2143	**0.1064**	0.3446	0.3322	0.1207	0.4409	0.1558	0.1511
2008	0.2050	0.3103	0.5322	0.5237	**0.1447**	0.1820	0.2338	0.2293	**0.1023**	0.3605	0.3523	0.1163	0.4432	0.1616	0.1592
2009	0.2030	0.2885	0.3938	0.3845	**0.1438**	0.1662	0.1739	0.1688	**0.0984**	0.2568	0.2497	0.1057	0.3486	0.1306	0.1278
2010	0.2030	0.2882	0.3930	0.3834	**0.1460**	0.1681	0.1740	0.1690	**0.1071**	0.2564	0.2494	0.1114	0.3525	0.1327	0.1300
2011	0.2028	0.2886	0.3941	0.3855	**0.1444**	0.1677	0.1742	0.1699	**0.1064**	0.2576	0.2514	0.1100	0.3545	0.1313	0.1290
2012	0.2029	0.2885	0.3929	0.3831	**0.1436**	0.1683	0.1744	0.1692	**0.1036**	0.2570	0.2497	0.1087	0.3502	0.1306	0.1279
2013	0.2028	0.2882	0.3925	0.3826	**0.1434**	0.1661	0.1738	0.1686	**0.0985**	0.2561	0.2487	0.1055	0.3431	0.1304	0.1277

MSE Mean squared errors between estimated vs actual results for 2014

Cell colors refer to criteria selection in Tables 3 and 4. Bold numbers are best performer models in each group per year

following the same format as in Tables 3 and 4. The predictive power of these models is presented in Table 6

It should be noted that none of these models fulfill all the criteria stipulated previously. Moreover, most of the models do not comply with any of the requirements, and only model C5 surpasses the condition of statistical significance for several years. Also, the fit of the models is over 50% in almost all cases. This situation is similar to what is observed in models 'A' and 'B', in the sense that adding new terms to the regression only partially improve its adj. R^2 but worsening their performance in the other selection variables. The same could be said about their out-of-sample predictive power (Table 8); the MSE tends to diminish with respect to models 'A' and 'B', but only marginally and in detriment of the other criteria.

Nevertheless, a pattern could be identified in these results too: ***PLand***^{2}, ***NIEF***, and ***NIEF***^{2} terms are not statistically significant when the interaction term is present on the model (which is always statistically significant). Conversely, the parameter of the ***PLand*** variable comply with this criterion when it is contained with the interaction term, suggesting it is the best choice to complement the term ***PLand*NIEF*** in the regressions. This strengthens the results obtained by model B4.

Comparing the results in Tables 3, 4, 6, and 7 (and Tables 5 and 8), it could be concluded that model B4, even being simpler than (probably over specified) models with three or more variables, provides similar or better results. When this is not true, the difference in adj. R^2 is less than 4% and less than 0.0200 in predictive power. Though, model B4 does not comply with the sign criterion for the ***PLand*** parameter, being always negative. This could have mainly two reasons: the first is that the attraction of mining investments cannot be explained by the selected proxies in a polynomial function of second degree, and thus, it is necessary to use other proxies or a nonlinear relationship between them; the second one is that there is one or more structural breaks in the datasets or in the market's behavior.

The investment climate threshold and the structural break model

Based on the results obtained for models 'A' to 'E', and the shortcomings identified in them, a new model is proposed, which is named the "structural break model". This conceptualization assumes the presence of a threshold in the ***NIEF*** variable. For countries with NIEF lower than this limit, mining competitiveness is defined by the interaction term ***PLand*NIEF***; for countries having higher investment climate, mining attractiveness is solely dependent on their natural endowment (**PLand**).

To represent this threshold and behavioral change, it is necessary to introduce a dummy variable ***Dx*** in the model. This variable takes the value zero when the ***NIEF*** value for

Table 6 Adjusted R^2 and criteria selection for models 'C', 'D', and 'E'

Year	C1	C2	C3	C4	C5	C6	D1	D2	D3	D4	E
1996	**0.7174**	0.6752	0.6752	0.6879	0.6887	0.4894	**0.7112**	**0.7112**	0.6682	0.6817	0.7044
1997	**0.7129**	0.6936	0.6939	0.6884	0.6920	0.528	0.709	**0.7101**	0.6943	0.6918	0.7091
1998	**0.7000**	0.6631	0.6621	0.6553	0.6589	0.4839	0.6944	**0.6946**	0.6657	0.6605	0.6945
1999	**0.7471**	0.7239	0.7212	0.6818	0.6902	0.5020	0.742	0.7421	0.7385	0.701	**0.7542**
2000	**0.7645**	0.7584	0.7568	0.7004	0.7063	0.5454	0.7605	0.7600	0.7664	0.7132	**0.7678**
2001	**0.7109**	0.7042	0.7044	0.6850	0.6880	0.5206	0.708	**0.7086**	0.6986	0.6851	0.7032
2002	0.7313	0.7333	**0.7337**	0.6887	0.6923	0.5858	0.7277	0.7283	**0.7292**	0.6907	0.7236
2003	0.7333	0.7345	**0.7346**	0.6656	0.6687	0.5546	**0.7293**	**0.7293**	**0.7293**	0.6666	0.7238
2004	0.7674	0.7680	**0.7681**	0.7139	0.7168	0.6231	0.7643	**0.7645**	0.7637	0.7151	0.7600
2005	0.7639	**0.7642**	0.7641	0.7136	0.7154	0.6523	**0.7604**	0.7603	0.7599	0.7125	0.756
2006	0.7467	**0.7468**	0.7467	0.7126	0.7133	0.6475	0.7428	0.7426	**0.7429**	0.7086	0.7386
2007	0.7783	**0.7784**	0.7784	0.7246	0.7263	0.663	**0.7747**	0.7746	**0.7747**	0.7232	0.7709
2008	0.7964	0.7982	**0.7987**	0.755	0.7592	0.6976	0.7948	0.7953	**0.7965**	0.7627	0.7932
2009	**0.7537**	0.7525	0.7529	0.7309	0.7335	0.6886	0.7521	**0.7525**	0.7522	0.7362	0.7521
2010	**0.8023**	0.7998	0.7999	0.7545	0.7580	0.6690	0.8006	0.8007	0.7997	0.7642	**0.8011**
2011	**0.8257**	0.8237	0.8240	0.7720	0.7763	0.6905	0.8241	0.8244	0.8246	0.7858	**0.8256**
2012	**0.8178**	0.8145	0.8148	0.7741	0.7776	0.6827	0.8171	0.8176	0.8156	0.7836	**0.8188**
2013	**0.7787**	0.7744	0.7752	0.7605	0.7640	0.7110	0.7785	0.7798	0.7820	0.7742	**0.7866**
2014	**0.7731**	0.7665	0.7674	0.7630	0.7660	0.7178	0.7739	0.7753	0.7756	0.7742	**0.7822**

the country analyzed is above the defined limit and takes the value of one when the ***NIEF*** value is below the defined limit. Thus, the model is expressed as follows:

$$\begin{aligned} \boldsymbol{PExpl_i} &= \boldsymbol{f}\ (\boldsymbol{PLand_i}, \boldsymbol{NIEF_i}) + \varepsilon_i \\ &= \phi_0 + \phi_1 \boldsymbol{PLand_i d_{x,i}} \\ &\quad + \phi_2 \boldsymbol{PLand_i NIEF_i}(\boldsymbol{1}-\boldsymbol{d_{x,i}}) + \varepsilon_i \end{aligned} \tag{5}$$

$$D_{x,i} \begin{cases} 0 \text{ if } NIEF_i < \text{x}, & \text{being } 0 < \text{x} < 1 \\ 1 \text{ if } NIEF_i \geq \text{x}, & \text{being } 0 < \text{x} < 1 \end{cases}$$

Table 7 Structure of models 'C', 'D', and 'E'

	C1	C2	C3	C4	C5	C6	D1	D2	D3	D4	E
β0	β0	β0	β0	β0	β0	β0	β0	β0	β0	β0	β0
PLand	β1	β1	β1				β1	β1	β1		β1
PLand²	β2			β2	β2		β2	β2		β2	β2
NIEF		β3		β3		β3	β3		β3	β3	β3
NIEF²			β4		β4	β4		β4	β4	β4	β4
PLand x NIEF	β5	β5	β5	β5	β5	β5	β5	β5	β5	β5	β5

The optimal value of ***NIEF*** that defines the structural break for each year is obtained running several regressions with the threshold changing in a range between 0.2 to 0.9 ($0.20 \leq x \leq 0.90$). Therefore, the definitive threshold of a particular year is the one included in the regression that maximizes the adj. R^2. In the case that the maximum fit is reached for a range of '*x*' values, the median is assigned. Then, this final functional form is tested against the same criteria selection of the previous models. If the model does not comply with all the criteria, a search is performed for other values of '*x*' that allow to fulfill the criteria selection.

The structural break may be due to the behavior of mining companies when investing at countries with different levels of investment climate. In general, for a constant geological potential with a relatively unattractive investment climate, companies prefer safer countries (with a better investment climate) to place their investments. However, as countries with better investment climate are compared (for a constant geological potential), the companies' behavior changes and the location of investments depends almost exclusively on the geological potential of the selected territory. In fact, when ordering the data of a representative year (2012) in a $\boldsymbol{NIEF_i}$ vs $\boldsymbol{PExpl_i}$ plot (Fig. 1), it could be observed that the dependent variable seems unrelated to the independent one for higher values of the latter.

Table 8 Predictive power of models 'C', 'D', and 'E' (MSE × 1000)

Year	C1	C2	C3	C4	C5	C6	D1	D2	D3	D4	E
1996	**0.1471**	0.1607	0.1612	0.1526	0.1540	0.3156	**0.1473**	**0.1473**	0.1614	0.1554	**0.1473**
1997	0.1266	0.1418	0.1430	**0.1262**	0.1290	0.2312	**0.1271**	0.1279	0.1473	0.1371	0.1326
1998	0.1480	0.1684	0.1684	**0.1297**	0.1316	0.2219	0.1479	0.1473	0.1711	**0.1419**	0.1511
1999	0.1965	0.2467	0.2432	**0.1493**	0.1591	0.2786	0.1984	0.1948	0.2575	**0.1932**	0.2171
2000	0.1597	0.1819	0.1803	**0.1333**	0.1381	0.2224	0.1621	0.1598	0.1884	**0.1559**	0.1713
2001	**0.1175**	0.1341	0.1340	0.1280	0.1292	0.1870	0.1193	0.1192	0.1325	0.1296	**0.1179**
2002	**0.1183**	0.1212	0.1214	0.1343	0.1355	0.1807	0.1203	0.1202	0.1194	0.1341	**0.1178**
2003	**0.1452**	0.1467	0.1462	0.1473	0.1478	0.1863	0.1481	0.1474	0.1459	**0.1456**	0.1471
2004	**0.1227**	0.1279	0.1275	0.1300	0.1294	0.1609	0.1241	0.1235	0.1264	0.1253	**0.1221**
2005	0.1082	0.1057	**0.1051**	0.1105	0.1086	0.1396	0.1089	0.1082	0.1065	**0.1029**	0.1109
2006	**0.1007**	0.1027	0.1023	0.1048	0.1027	0.1331	0.1003	**0.0999**	0.1062	0.1005	0.1037
2007	0.1071	0.1065	**0.1063**	0.1173	0.1151	0.1369	0.1071	**0.1069**	0.1079	0.1099	0.1088
2008	**0.1028**	0.1040	0.1037	0.1148	0.1139	0.1418	0.1039	0.1033	0.1002	0.1062	**0.0993**
2009	**0.0962**	0.0980	0.0977	0.0998	0.0985	0.1204	0.0953	0.0948	0.0954	0.0950	**0.0924**
2010	0.1044	0.1072	0.1070	0.1050	**0.1037**	0.1229	0.1041	0.1037	0.1047	**0.1005**	0.1011
2011	0.1039	0.1064	0.1062	0.1036	**0.1023**	0.1225	0.1036	0.1031	0.1033	**0.0992**	0.1000
2012	**0.1007**	0.1034	0.1031	0.1024	0.1011	0.1201	0.1000	0.0995	0.1005	0.0976	**0.0968**
2013	**0.0954**	0.0981	0.0978	0.0995	0.0982	0.1186	0.0944	0.0938	0.0937	0.0940	**0.0902**

MSE Mean squared errors between estimated vs actual results for 2014

Cell colors refer to criteria selection in Tables 6 and 7. Bold numbers are best performer models in each group per year

This behavior could be simply due to the heteroscedasticity of the datasets or the presence of a threshold value (graphically shown as a dashed line in Fig. 1). Therefore, the structural break model corresponds to an intermediate situation between model A1 and A5, for low and high values of 'x' respectively. For very low values of 'x', all countries are above the climate investment threshold, so mining competitiveness depends exclusively on ***PLand***. Likewise, for very high values, no country is considered safe enough, so the attraction of mining investments depends on the interaction term.

When applying the structural break model, the adj. R^2 value increases compared to models A1 and A5. Figure 2 shows the fit of the structural break model for year 2012 when varying the 'x' value. In this case, the highest adj. R^2 is obtained when x is 0.64–0.65 and 0.77–0.78, reaching an adj. R^2 of 0.82.

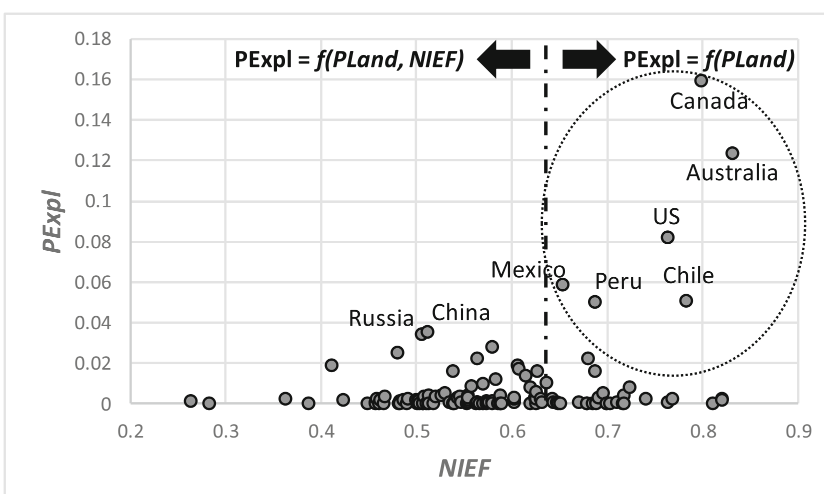

Fig. 1 NIEF vs PExpl for the year 2012

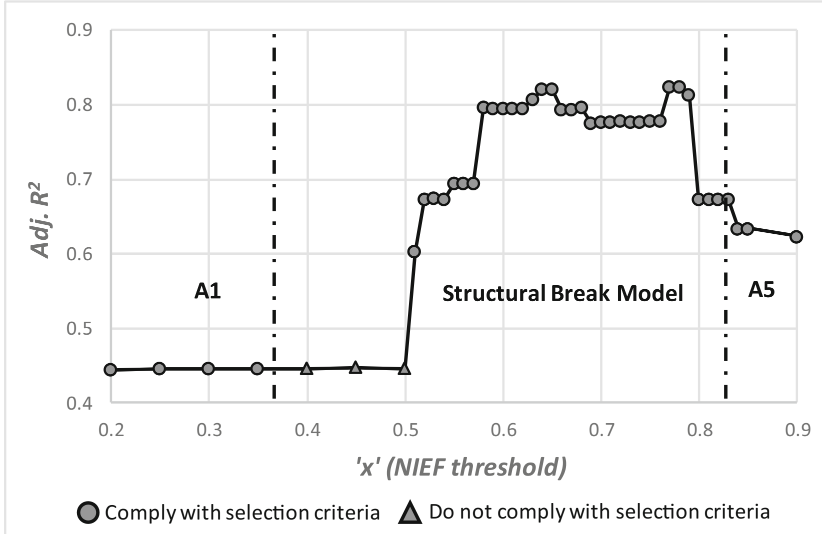

Fig. 2 Impact of the '*x*' value in the performance of the structural break model

In Table 9, the results for the structural break model for the entire study period are shown. For each year, the adj. R^2, the threshold value '*x*', and the estimated parameters are reported. The latter are subject to the same background colors for the criteria selection used in the previous tables. Finally, the last two columns present the number of observations (countries) below and above the investment climate threshold.

Table 9 Results for the structural break model

Year	adj. R^2	'x'	β_0	β_1	β_2	Obs. (n)	
						Above '*x*'	Below '*x*'
1996	0.5439	0.74	0.006	1.685	0.760	4	44
1997	0.5655	0.73	0.006	1.611	0.754	5	53
1998	0.5615	0.74	0.007	1.703	0.669	4	55
1999	0.6117	0.70	0.007	1.840	0.572	6	48
2000	0.5637	0.73	0.005	1.738	0.857	5	53
2001	0.4959	0.73	0.005	1.488	0.954	5	48
2002	0.7589	0.62	0.002	1.682	0.479	23	30
2003	0.7808	0.64	0.003	1.856	0.433	19	36
2004	0.8322	0.64	0.003	1.779	0.539	18	39
2005	0.8202	0.65	0.004	1.629	0.634	11	49
2006	0.7999	0.62	0.003	1.575	0.680	20	42
2007	0.8363	0.62	0.002	1.795	0.671	22	42
2008	0.8293	0.63	0.003	1.725	0.606	19	46
2009	0.7760	0.63	0.002	1.581	0.801	38	80
2010	0.8093	0.65	0.002	1.776	0.636	31	88
2011	0.8166	0.66	0.002	1.714	0.602	29	86
2012	0.8217	0.65	0.002	1.662	0.601	31	93
2013	0.7815	0.67	0.002	1.515	0.752	29	94
2014	0.7739	0.66	0.002	1.489	0.809	32	90

Every year, the structural break model (SBM) outperforms the results obtained when comparing with model A5, the best model with only one independent variable. The SBM even surpasses the fit of models B4 after 2002 but fulfilling all the criteria selection. The model goodness of fit (adj. R^2) substantially improves after 2001. This phenomenon could be explained by (i) the quality of the exploration budget dataset, which has improved over time covering more countries and companies each year, and (ii) the changes in the global geopolitical situation and the financial markets, with the globalization process exploding at the end of the 1990s. The same reasons could be said to describe the high threshold value before 2002; the investment climate indices for much of the developing countries improved after the globalization of democracy and free markets during the 1990s. Additionally, the lowest '*x*' values overlap the so called "commodities supercycle", possibly because mining companies were able to assume higher investments risks during high prices periods. Also, the second half of the 1990s (Asian crisis) and the time after 2009 (subprime crisis) were marked by economic uncertainty and by high or increasing investment climate thresholds, respectively.

The estimated β_0 parameters do not fulfill the statistical significance every year but for the last three regressions (2012–2014). This value represents a "basal mining competitiveness" for countries having null geological potential and zero investment climate. Economic theory and common thinking suggest that a country with these characteristics should not capture any investment for mining activities. Therefore, in every model, β_0 must be close to zero and/or statistically irrelevant, which is the case for the structural break models. Regarding β_1 and β_2, the results are highly consistent through time. In fact, their average values are 1.676 and 0.674, and their standard deviation are 0.112 and 0.131 respectively.

It is important to notice that the estimated parameters (‘x’ and β_i) change year by year as a result of the natural fluctuations of the exploration and mining markets. However, these changes are smooth due to the inertia of those economic sectors (the mining business is characterized by high initial investments, long-standing operations and delayed returns over the capital employed; Jara et al. 2008). Thus, the stability of the estimated parameters for these models is another expected result. To corroborate this finding, Table 10 presents the results of a 5-year rolling regression process ran for the SBM using the average ‘x’ value for each the period.

Taking the structural model of the year 2012, which has estimated parameters close to the average ones, the marginal impacts of the geological potential and the investment climate can be calculated as follows:

$$\frac{d\boldsymbol{PExpl}}{d\boldsymbol{Pland}} = \begin{cases} 0.601{*}\boldsymbol{NIEF} & \textit{if } \boldsymbol{NIEF} < 0.65 \\ 1.662 & \textit{if } \boldsymbol{NIEF} \geq \boldsymbol{0.65} \end{cases} \tag{6}$$

$$\frac{d\boldsymbol{PExpl}}{d\boldsymbol{NIEF}} = \begin{cases} 0.601{*}\boldsymbol{Pland} & \textit{if } \boldsymbol{NIEF} < 0.66 \\ 0 & \textit{if } \boldsymbol{NIEF} \geq \boldsymbol{0.66} \end{cases} \tag{7}$$

Equation 6 shows that a marginal increase in the geological potential of a country located below the threshold depends on the investment climate and is higher for countries having better ***NIEF***. However, for countries above this limit the impact is independent of the investment climate and is much higher than for the former ones. For example, an increase of 1% in the geological potential of China (***NIEF*** = 0.51 in 2012) implies a growth of 0.31% in its percentage of global exploration budgets (= 0.60 × 0.51). The same improvement in the perception of the natural endowment of Chile should result in an additional 1.66% of total exploration investment, independent of its investment climate (***NIEF*** = 0.78 in 2012). Regarding Eq. 7, a similar outcome is obtained for countries having lower ***NIEF*** values. However, countries above the threshold see no gains in mining competitiveness for improving their business environs. For example, taking these two countries, a 1% improvement of China’s investment climate (***PLand*** = 0.0768 in 2012) should make the Asian country obtain 0.0462% more mining investments (= 0.60 × 0.0768); contrastingly, for Chile, a 1% improvement in investment climate should make no difference in its share of global exploration budgets.

From a public policy perspective, the independence of mining competitiveness with respect to the investment climate for countries having high economic freedom is a risky conclusion. If that is the case, those countries could be incentivized to deter their investment environs until they reach the investment climate threshold (for example, increasing the mining tax burden) without seeing a reduction in their investment attraction. Of course, this is not the actual case. This result could be due to the oversimplification of the linear econometric model, which could be not considering all the complexity of company behavior in the transition zone between the two specific models (models A1 and A5) just by including a structural break.

Table 10 Results of the rolling regression process for the structural break model

Period	adj. R^2	‘x’	β_0	β_1	β_2	Obs. (n)
1996–2000	0.5781	0.73	0.006	1.717	0.725	277
1997–2001	0.5637	0.73	0.006	1.674	0.767	282
1998–2002	0.6837	0.70	0.007	1.677	0.478	277
1999–2003	0.7415	0.68	0.006	1.673	0.332	273
2000–2004	0.7621	0.67	0.005	1.705	0.417	276
2001–2005	0.7681	0.66	0.005	1.690	0.495	278
2002–2006	0.7709	0.63	0.003	1.633	0.545	287
2003–2007	0.7842	0.63	0.003	1.651	0.584	298
2004–2008	0.8175	0.63	0.003	1.689	0.638	308
2005–2009	0.8098	0.63	0.002	1.655	0.689	369
2006–2010	0.8089	0.63	0.002	1.683	0.691	428
2007–2011	0.8087	0.64	0.002	1.711	0.680	481
2008–2012	0.8074	0.64	0.002	1.687	0.662	541
2009–2013	0.7973	0.65	0.002	1.647	0.687	599
2010–2014	0.7938	0.66	0.002	1.625	0.693	603

Discussion and recommendations

The results presented in this study support the (broadly accepted) alternative paradigm for the attraction of mining investments: in order to develop a local mining industry in a particular country or district, it is necessary to have a wealthy natural endowment and a good investment climate. Nevertheless, the research also shows that once public policies and other contextual variables reach reasonable levels (investment climate threshold), districts compete for mining investments almost exclusively based on their geological potential. This conclusion is based on the excellent performance obtained by the structural break models, especially for the years after 2001 (adj. $R^2 > 0.75$ and highly significant parameters). For the previous periods, these models are still good enough, outperforming all others with one independent variable (model A). With respect to the models incorporating two or more variables, the break models get similar fits than the better models but complying with the selection criteria defined before starting the analysis. This change in behavior in 2001/02 could be attributed to (i) the coverage and quality of the Metals Economic Group/SNL (MEG/SNL) and The Heritage Foundation datasets and (ii) the globalization of markets during the second half to the 1990s and early 2000s. Exploration companies, mainly from Australia and Canada, strongly increased their overseas presence during those decades. Previously, their focus was mainly on national territory or on highly safe countries. Thus, datasets were less representative of the world market.

Regarding the use of proxies for the geological potential and the investment climate, the index of economic freedom and the country land extension proved to be good choices for the whole study period, confirming the findings of Khindanova (2011) and of Jara (2017). Despite their utility to explain the attraction of mining investments, the use of these proxies could be questioned since they are not specific for the mining industry. The index of economic freedom does not take into account regulations particular for mining, or the existence or amount of mining royalties or any other specific condition that could determine the viability of a mining investment project. Also, the land extension of a country is a highly stable indicator (in this study, this varies mostly due to the entrance/exit of countries into the exploration market), but the perception of its geological potential could change smoothly or even abruptly. The continuous development and release of precompetitive geological information by the geological service of a country can slowly increase its geological potential; meanwhile, a world class discovery can achieve an increase in a short time. Conversely, the exploitation and depletion of its best mineral resources could diminish the perception of geological potential because of the perception that its territory is mature in terms of exploration. It is not real that every km^2 of a country has the same geological potential because particular geological conditions make some areas more interesting than others. Therefore, to deal with these issues, it would be necessary to do an analysis by mineral commodity, and ideally by type of company (major, intermediate, and junior) since they are affected in different ways along the business cycle. For example, including other proxies like the effective tax rate applicable to mining in each jurisdiction or the production and head grades of current operations. This would allow to improve the legitimacy of the models developed in Jara (2017) and in this study (this does not justify maintaining the current proxies but to complement them by incorporating mining specific variables).

Another area of improvement of the structural break model is related to its functional form. The abrupt change in the threshold is not appealing, even though its rationality seems correct. Probably a gradual decrease on the influence of the investment climate in the countries' mining competitiveness when those jurisdictions are safer could better represent the actual behavior of companies. The geological potential being the only relevant variable to attract mining investments (over the investment climate threshold) is a risky representation of reality. If that is true, there is an incentive to countries above the threshold to pursue higher shares of the mining rent (for example increasing tax rates) until they reach the limit between both groups.

Acknowledgments This paper is an updated version of the MSc thesis developed by SD. This work was part of a contract research between Minera Los Pelambres (MLP) and the Pontificia Universidad Católica de Chile. The authors would like to acknowledge Mr. Magnus Ericsson, Editor-in-Chief of Mineral Economics and two anonymous reviewers for their helpful comments on an earlier version of this manuscript, which considerably improved it. JJJ and GL would like to thanks MLP and Antofagasta Minerals S.A. (AMSA) for their financial support and the access to SNL data that was critical to this study, in particular, to Christian Brea (Fundación MLP) and Rodrigo Moya (AMSA) for their kind support. JJJ acknowledges the support of a Doctoral Scholarship from Conicyt.

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