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UNIVERSITY OF SOUTHAMPTON

FACULTY OF SOCIAL AND HUMAN SCIENCES

Division of Economics

Essays on The Industrial Organization of The International Copper Industry

by

Andrés Luengo Morales

A thesis submitted in partial fulfillment for the degree of Doctor of Philosophy

August 2015

To my parents

UNIVERSITY OF SOUTHAMPTON

ABSTRACT

FACULTY OF SOCIAL AND HUMAN SCIENCES

SCHOOL OF ECONOMICS

Doctor of Philosophy

ESSAYS ON THE INDUSTRIAL ORGANIZATION OF THE INTERNATIONAL COPPER INDUSTRY

by Andrés Luengo Morales

The aim of this thesis is to study the main drivers of the supply of copper. This thesis proposes and estimates a dynamic structural model of the operation of copper mines using a unique dataset with rich information at the mine level from 330 mines that account for more than 85% of the world production during 1992-2010. It includes several aspects of this industry that have been often neglected by previous econometric models using data at a more aggregate level. First, there is a substantial number of mines that adjust their production at the extensive margin, i.e., temporary mine closings and re-openings that may last several years. Second, there is very large heterogeneity across mines in their unit costs. This heterogeneity is mainly explained by differences across mines in ore grades (i.e., the degree of concentration of copper in the rock) though differences in capacity and input prices have also relevant contributions. Third, at the mine level, ore grade is not constant over time and it evolves endogenously. Ore grade declines with the depletion of the mine reserves, and it may increase as a result of (lumpy) investment in exploration. Fourth, for some copper mines, output from sub-products (e.g., gold, silver, nickel) represents a substantial fraction of their revenue. Fifth, there is high concentration of market shares in very few mines, and evidence of market power and strategic behavior. Finally, sunk entry and exit costs are large and a key determinant of mine turnover. This sunk costs are also an important driver of prices. The proposed and estimated structural model in this thesis helps to understand better the dynamics of prices and extraction behaviour not only for the copper industry but to all extractive industries.

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Declaration of Authorship

I, Andrés Luengo, declare that the thesis entitled *Essays on The Industrial Organization of The International Copper Industry* and the work presented in the thesis are both my own, and have been generated by me as the result of my own original research.

I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
3. Where I have consulted the published work of others, this is always clearly attributed;
4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;

5. I have acknowledged all main sources of help;
6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
7. None of this work has been published before submission.

Signed: ....

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1

Introduction

Mineral natural resources, such as copper, play a fundamental role in our economies. They are key inputs in important industries like construction, electric materials, electronics, ship building, or automobiles, among many others. This importance has contributed to develop large industries for the extraction and processing of these minerals. In 2008, the world consumption of copper was approximately 15 million tonnes, grossing 105 billion dollars in sales, and employing more than 360.000 people (source: US Geological survey). The evolution and the volatility of the price of these commodities, the concern for the socially optimal exploitation of non-renewable resources, or the implications of cartels, are some important topics that have received substantial attention of researches in Natural Resource economics at least since the 70s. More recently, the environmental regulation of these industries and the increasing concern on the over-exploitation of natural resources have generated a revival of the interest in research in these industries.

Hotelling model (Hotelling, 1931) has been the standard framework to study topics related to the dynamics of extraction of natural resources. In that model, a firm should decide the optimal production or extraction path of the resource to maximize the expected and discounted flow of profits subject to a known and finite stock of reserves of the non-renewable resource. The Euler equation of this model establishes that, under the optimal extraction path, the price-cost margin of the natural resource should increase over time at a rate equal to the interest rate. This prediction, described in the literature as Hotelling's rule, is often rejected in empirical applications (Farrow, 1985; Young, 1992). Different extensions of the basic model have been proposed to explain this puzzle. Pindyck (1978) included exploration decisions: a firm should decide every period not only the optimal extraction rate but also investment in exploration. In contrast to Hotelling's rule, this model predicts that prices should follow a U-shaped path. Gilbert (1979) and Pindyck (1980) introduce uncertainty in reserves and demand. Slade and Thille (1997) propose and estimate a model that integrates financial and output information and finds a depletion effect that is consistent with Hotelling model. Krautkraemer (1988) presents a comprehensive review of the literature, theoretical and empirical, on extensions of the Hotelling model.

Hotelling model and the different extensions are models for the optimal behavior production and investment decisions of a mine. The predictions that these models provide should be tested at the mine level because they involve mine specific state variables. An important limitation in the literature comes from the data that has been used to estimate these models. The type of data most commonly used in applications consists of aggregate data on output and reserves at the country or firm level with very limited information at the mine level. These applications assume that the 'in situ' depletion effects at the mine level can be aggregated to obtain similar depletion effects using aggregate industry data. However, in general, the necessary conditions for this "representative mine" model to work are very restrictive and they do not hold. This is particularly the case in an industry, such as copper mining, characterized by huge heterogeneity across mines in key state variables such as reserves, ore grade, and unit costs. Using aggregate level data to test Hotelling rule can be misleading. Perhaps most importantly, the estimation of aggregate industry models can generate important biases in our estimates of short-run and long-run responses to demand and supply shocks or to public policy changes.

In this thesis, we propose and estimate a dynamic structural model of the operation of copper mines using a unique dataset with rich information at the mine level from 330 mines that account for more than 85% of the world production during 1992-2010. Our descriptive analysis of the data reveals several aspects of this industry that have been often neglected in previous econometric models using data at a more aggregate level. First, there is a substantial number of small and medium size mines that adjust their production at the extensive margin, i.e., they go from zero production to positive production or vice versa. In most of the cases, these decisions are not permanent mine closings or new mines but re-openings and temporary closings that may last several years. Second, there is very large heterogeneity across mines in their unit costs. This heterogeneity is mainly explained by substantial differences across mines in ore grades (i.e., the degree of concentration of copper in the rock) though differences in capacity and input prices have also relevant contributions. Third, at the mine level, ore grade is not constant over time and it evolves endogenously. Ore grade declines with the depletion of the mine reserves, and it may increase as a result of (lumpy) investment in exploration. Fourth, there is high concentration of market shares in very few mines, and evidence of market power and strategic behavior.

We present a dynamic structural model that incorporates these features of the industry and the operation of a mine. In the model, every period (year) a mine manager makes two dynamic decisions: the decision of being active or not; and if active, how much output to produce. Related to these decisions, there are also four state variables at the mine level that evolve endogenously and can have important impacts on the mine costs. The amount of reserves of a mine is a key state variable because it determines the expected remaining life time, and may have also effects on operating costs. A second state variable is the indicator that the firm was active at previous period. This variable determines whether the firm has to pay a (re-) start-up cost to operate. The ore grade of a mine is an important state variable as well because it determines the amount of copper per volume of extracted ore. This is the most important determinant of a mine average cost because it can generate large differences in output for given amounts of (other) inputs. The cross-sectional distribution of ore grades across mines has a range that goes from 0.1% to more than 10%. There is also substantial variation in ore grades within a mine. This variation is partly exogenous due to heterogeneity in ore grades in different sections of the mine that are unpredictable to managers and engineers. However, part of the variation is endogenous and depends on the depletion/production rate of the mine. Sections of the mine with high expected ore grades tend to be depleted sooner than areas with lower grades. As a result, the (marginal) ore grade of a mine declines with accumulated output. Finally, the capacity or capital equipment of a mine is an important state variable. Capacity is measured in terms of the maximum amount of copper that a mine can produce in a certain period (year), and it is determined by the mine extracting and processing equipment, such as hydraulic shovels, transportation equipment, crushing machines, leaching plants, mills, smelting equipment, etc.[1] The model includes multiple exogenous state variables such as input prices, productivity shocks, and demand shifters.

The set of structural parameters or primitives of the model includes the production function, demand equation, the functions that represent start-up costs and fixed costs, the endogenous transition rule of ore grade, and the stochastic processes of the exogenous state variables. The production function includes as inputs labor, capital, energy, ore grade and reserves. Our dataset has several features that are particularly important in the estimation of the production function: data on the amounts of output and inputs are in physical units; we have data on input prices at the mine level; data on output distinguishes two stages, output at the extraction stage (i.e., amount of extracted ore), and output at the final stage (i.e., amount of pure copper produced). We present estimates of a production function using alternative methods including dynamic panel data methods Arellano and Bond (1991) and Blundell and Bond (2000), and control function methods (Olley and Pakes, 1996; Levinsohn and Petrin, 2003). For the estimation of the transition rule of ore grade, we also present estimates based on dynamic panel methods.

[1] Capacity is equivalent to capital equipment but it is measured in units of potential output.

The estimation of the structural parameters in the functions for start-up costs and fixed costs in chapter 7, is based on the mine's dynamic decision model. The large dimension of the state space, with twelve continuous state variables, makes computationally very demanding the estimation of the model using full solution methods (Rust, 1987) or even two-step / sequential methods that involve the computation of present values (Hotz and Miller, 1993; Aguirregabiria and Mira, 2002). Instead, we estimate the dynamic model using moment conditions that come from Euler equations for each of the decision variables. For the discrete choice variables (i.e., entry/exit and investment/no investment decisions), we derive Euler equations using the approach in Aguirregabiria and Magesan (2013, 2014). For the Euler equation of the output decision, we construct moment conditions and a GMM estimator in the spirit of Hansen and Singleton (1982).

The *GMM-Euler equation* approach for the estimation of dynamic discrete choice models has several important advantages. First, the estimator does not require the researcher to compute or approximate present values, and this results into substantial savings in computation time and, most importantly, in eliminating the bias induced by the substantial approximation error of value functions when the state space is large. Second, since Euler equations do not incorporate present values and include only optimality conditions and state variables at a small number of time periods, the method can easily accommodate aggregate shocks and non-stationarities without having to specify and estimate the stochastic process of these aggregate processes.

In this model, the derivation of Euler equations has an interest that goes beyond the estimation of the model. Hotelling rule is the Euler equation for output in a simple dynamic model for the optimal depletion of a non-renewable natural resource where the firm is a price taker, it is always active, ore grade is constant over time, reserves and ore grade do not affect costs, and there are no investments in capacity or/and explorations. The Euler equations relax all these assumptions. The comparison of our Euler equations with Hotelling rule provides a relatively simple way to study and to measure how each of the extension of the basic model contribute to the predictions of the model.

The estimates quantifies many important determinants of the structure of the industry. First, there is an important dynamic role of the depletion effect. By doubling current output ore grades depreciates by 7%. In addition, for the average mine, the depletion effect represents 5% of marginal costs. Second, from our production function estimates, we find that the industry presents constant returns to scale and substantial economies of scale. The technology in this industry is very intensive in capital and energy but not in labor. This is the reflect of a modern mining with high qualified labor. Third, we find that some mines enjoy large markups. This is due to large heterogeneity in geological characteristics across mines which affect the exogenous part of their marginal costs. For example, if we eliminate the variability of the ore grade, all the rest constant, the variance of marginal costs would decline by 58%. Fourth, price is mainly determined by demand factors. Our model shows that positive (negative) shocks in demand leads to temporary entry (exit) of small and less efficient mines. In general, the productivity of the industry grown up by 7%, 43% of this increase is explained by a reallocation effect. Fifth, there is robust evidence of market power and strategic behaviour. Conjectural Variation estimates reject a competitive pricing and suggest Cournot oligopoly as the more likely result. This is an important result as the literature of natural resources typically assumes that commodity markets are perfectly competitive. Sixth, market power cannot explain all the volatility observed on prices, however, if we shut down market power, price would decline, in average, by 19%. We observe a lower impact of the depletion effect on prices. By eliminating the depletion effect, price would decline by 1.3%. Finally, estimates of our structural model suggest that the average entry cost is about of 3.8 billions of dollars. This implies that the average mine recovers its initial investment in almost 10 years. Start-up costs have a strong implication in price dynamics, for instance, an increase of 10% in entry costs would lead to an increase of 43% in the average price. In addition, environmental regulation could play an important role in exit decisions, we observe a non-negligible exit value of almost 140 millions of dollars for the average mine. This is an interesting topic for further research.

The rest of this thesis is organized as follows. Chapter 2 provides a description of copper mining industry (history, extraction of processing techniques, geographic location of mines and market structure). Chapter 3 presents relevant literature on economics of natural resources and presents the main model of the thesis. In this chapter, we derive

Euler equations for the different decision variables, both continuous and discrete. Chapter 4 describe the dataset and presents the stylized facts of this industry that motivate the different extensions in the model. Chapter 5 presents the heterogeneity of ore grades and describes the depletion effect. Chapters 6 and 7 describes the structural estimation and econometric issues and present the main results of this thesis. Chapter 8 concludes.

2

The Copper Mining Industry

2.1 Brief History of the Copper Mining Industry

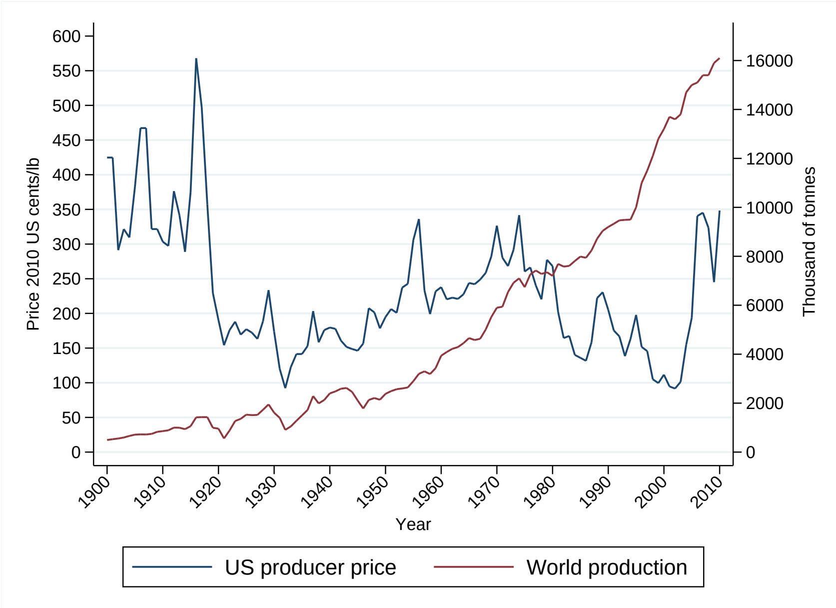
The earliest usage of copper dates from prehistoric times when copper in native form was collected and beaten into primitive tools by stone age people in Cyprus (where its name originates), Northern Iran, and the Lake region in Michigan (Mikesell, 2013). The use of copper increased greatly since the invention of smelting around the year 5000 BP, where copper ore was transformed into metal, and the development of bronze, an alloy of copper with tin. Since then until the development of iron metallurgy around 3000 BP, copper and bronze were widely used in the manufacture of weapons, tools, pipes and roofing. In the next millennium, iron dominated the metal consumption and copper was displaced to secondary positions. However, a huge expansion in copper production took place with the discovery of brass, an alloy of copper and zinc, in Roman times reaching a peak of 16 thousand tonnes per year in the 150-year period straddling the birth of Christ

(Radetzki, 2009). Romans also improved greatly the extraction techniques of copper. For instance, they implement the pumping drainage and widened the resource base from oxide to sulfide ores by implementing basic leaching techniques for the sulfide ores. After the fall of the Roman Empire, copper and all metals consumption declined and production was sustained by the use of copper in the manufacture of bronze cannons for both land and naval use, and as Christianity spreads for roofing and bells in churches (Radetzki, 2009).

The industrial revolution in the half eighteenth century marked a new era in mining and usage for all metals. However, copper did not emerge until 100 years later with the growth of electricity. The subsequent increased demand for energy and telecommunications led to an impressive growth in the demand for copper, e.g., in 1866 a telegraph cable made of copper was laid across the Atlantic to connect North America and Europe; ten years later the first message was transmitted through a copper telephone wire by Alexander Graham Bell; in 1878 Thomas Alva Edison produced an incandescent lamp powered through a copper wire (Radetzki, 2009). In 1913, the International Electrotechnical Commission (IEC) established copper as the standard reference for electrical conductivity. From that time until now, the use of copper has spread to different industrial and service sectors, but still half of the total consumption of copper is related to electricity. Copper wires have been used to conduct electricity and telecommunications across long distances as well as inside houses and buildings, cars, aircrafts and many electric devices. Copper's corrosion resistance, heat conductivity and malleability has made it an excellent material for plumbing and heating applications such as car radiators and air conditioners, among others (Radetzki, 2009).

The evolution of the copper industry has also historically been closely related, from a macroeconomic point of view, to the economic activity in developed countries and the international political scene. Figure 2.1 shows how the evolution of price and production has been affected by factors such as: world wars, political reasons (mainly in South America and Africa, which resulted in the nationalization of several U.S. copper operators in the 1960s and 1970s), the great depression, the Asian crisis and recently the subprime crisis.

Figure 2.1: World Copper Industry 1900 - 2010



Source: U.S. Geological Survey.
Deflator: U.S. Consumer Price Index (CPI). 2010 = 100

Until the late 1970s, the United States dominated the global copper industry. In 1947 it accounted for 49% of the world copper consumption and 37% of the world copper mine production, whereas in 1970 it consumed 26% of world copper and produced the 27%. However, the copper production controlled by the American multinational companies outside the US declined because of successive strikes, the 1973 oil crisis, and the nationalization processes in Zambia, Zaire, Peru and Chile. Since 1978 the copper industry has been characterized by several changes in ownership and geographical location.[1] The London Metal Exchange (LME) price has been adopted as the international price reference by producers and the market structure has experienced a consolidation era, where a few large companies have dominated this market.

[1]As deposits are depleted, mining shifts to countries with the next best deposits. In the absence of new discoveries and technological change, this tendency to exploit poorer quality ores tends to push productivity down and the prices of mineral commodities up over time.

2.2 Copper Production Technology

A copper mine is a production unit that vertically integrates the extraction and the processing (purification) of the mineral.[2] At the extraction stage, a copper mine is an excavation in earth for the extraction of copper ores, i.e., rocks that contain copper-bearing minerals. Copper mines can be underground or open-pit (at surface level), and this characteristic is pretty much invariant over time.[3] Most of the rock extracted from a copper mine is waste material. The ore grade of a mine is roughly the ratio between the pure copper produced and the amount of ores extracted. In our dataset, the average ore grade is 1.2% but, as we illustrate in chapter 5, there is large heterogeneity across mines, going from 0.1% to 11% ore grades.[4] Other important physical characteristic of a mine is the type of ore or minerals that copper is linked to: sulfide ores if copper is linked with sulfur, and oxide ores when copper is linked with either carbon or silicon, and oxygen. Although a mine may contain both types, the technological process typically depends on the main type of the ore. The type of ore is relevant because they have substantial differences in ore grades and volume of the reserves and because the processing technology is very different. Sulfide copper deposits have the lowest grade or copper content. However, sulfide deposits are very attractive for mining companies because their large volume, that allows exploiting economies of scale. On the other hand, although oxide deposits are smaller in volume, they have higher ore grade and their processing and purification implies a much lower cost than sulfide ores. Sulfide ores represent most of the world's copper production (80%).

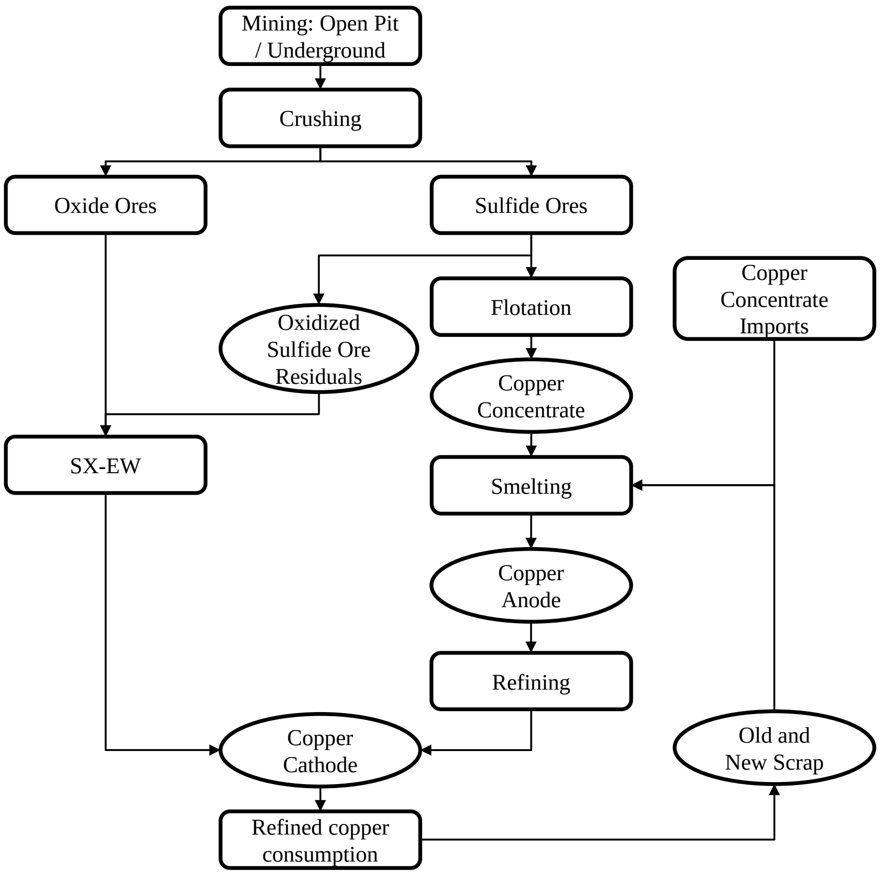
The production process of copper can be described mainly in three stages: extraction, concentration, and a purification process. In the extraction process copper ore can be mined by either open pit or underground methods. Independently of the extraction method, copper ores and other elements are extracted from the mine through digging

[2] As explained below, mines differ on the level of vertical integration.

[3] Some open-pit mines may eventually become underground, but this possible event occurs only once in the long lifetime of a copper mine.

[4] This final ore grade includes the recuperation rate that is the ratio between the ore grade at the end of production process and the ore grade after extraction and before the purification process. In our dataset the mean recuperation rate is 73.3%.

Figure 2.2: Copper Production Technology



and blasting, then they are transported out of the mine and finally crushed and milled. The concentration and refining processes depend on whether the ore is sulfide or oxide. In the first case, sulfide ores are converted into copper concentrates with a purity varying from 20% to 50% by a froth flotation process. In the purification stage, copper concentrates are melted removing unwanted elements such as iron and sulfur and obtaining a blister copper with a purity of 99.5%. Next, these blister copper are refined by electricity or fire eliminating impurities and obtaining a high-grade copper cathode with a purity of 99.9%. Typically, smelting and refining (or only refining) are carried out at smelter and refinery plants, different from the mine, either at the same country of the mine or in the final destination of the copper. High-grade copper is more easily extracted from oxide ores. In this case, refined copper is extracted in a two-stage hydrometallurgical process, so-called solvent extraction-electrowinning (SX-EW), where copper ores are first stacked and irrigated with acid solutions and subsequently cleaned by a solvent extraction process obtaining an organic solution. Next, in the refining process, copper with a grade of 99.9% is recovered from the organic solution by the application of electricity in a process called electrowinning. The final product for industrial consumption and sold in local or international markets is a copper cathode with a purity of 99.9%. As we describe in section 2.3, the SX-EW technology also allows to process residual ores (low ore grade) or waste dumps in mines from sulfide ores which have been oxidized by exposure to the air or bacterial leaching. Figure 2.2 describes the technological process of the copper production.

2.3 Technological Change

As noted in section 2.1, the industrial revolution also had an impact on the technology of mining. There have been important breakthroughs in mining techniques that have allowed not only to reduce production costs but to increase the resource reserves, reducing the fear of exhaustion. Probably, the two most important breakthroughs took place in a very short time. First, by 1905 the mining engineer Daniel C. Jackling, first introduced the mass mining at the Bingham Canyon open-pit mine in Utah (Mikesell, 2013). Mass mining applied large scale machinery in the production process, e.g., the use of steam shovels, heavy blasting, ore crushers, trucks and rail made profitable the exploitation of low-grade sulfide ores through economies of scale. The second most important development was the flotation process, created in Britain and first introduced in copper in Butte, Montana in 1911 (Slade, 2013b). This process, which is used to concentrate sulfide ores, improved significantly the recovery rates of metal and in turn lowered the processing costs. By 1935, recovery rates increased to more than 90% from the 75% average recovery rate observed in 1914 (McMahon, 1965).

Once open-pit mining, heavy blasting and flotation techniques were more practicable, the exploitation of low-grade sulfide deposits became economically profitable. By the beginning of the twentieth century most of the copper exploited came from selective mining where high grade veins were extracted and mass mining was not possible because of high loss of metal. The average grade of copper ore decreased greatly as large scale mining was introduced, while at the beginning of the twentieth century the average grades were close to 4%, by 1920s they had fallen to less than 2%. Despite this decrease in ore grades, production costs also declined in this period. The costs in 1923 decline at least 20% compared with those in 1918. Moreover, between 1900 and 1950 world copper output was quintupled, raising from 490 Kt. in 1900 to 2490 Kt. in 1950, in response to the explosive demand and the new mining techniques that increased mining production (Radetzki, 2009).

A third important breakthrough was the improvement in leaching techniques for oxide ores by the introduction in 1968 of the SX-EW process for copper at the Bluebird mine in Arizona. This process, as described above, allows to extract high-grade copper by applying acid solutions to oxide ores. Before the SX-EW process were introduced oxide ores were treated by a combination of leaching and smelting processes. The SX-EW process presents a number of advantages compared with the more traditional pyrometallurgical process, e.g., it requires a lower capital investment and faster start-up times, allow to process lower grade ores and mining waste dumps (Radetzki, 2009). The application of this process has spread greatly in recent decades. Between 1980 and 1995, the U.S. production by this method increased from 6% to 27% (Tilton and Landsberg, 1999). The SX-EW has also spread at international level. In 1992, this process accounted for the 8% of the world production and by 2010 its participation increased to 20% (Cochilco, 2001, 2013).

2.4 Geographical Distribution of World Production

As noted above, since the industrialization of mining until the late 1970s, the United States dominated the world industry. In the decade of 1920s, the U.S. copper industry reached its peak. By 1925, the United States produced 52% of the world's copper, while developing countries in Latin America, Africa and communist countries, produced 31%. This proportion was gradually reversed over time and by 1960 the U.S. world production rate had declined to 24% while that developing countries produced 40%. Africa accounted only about 7% by 1925, but by 1960 Africa, mainly by Zambia (14%), produced the 56% (Mikesell, 2013). In 1982, the United States produced the 16.23% while Chile, that between 1925 and early 1970s had accounted for the 15% of the world production, produced the 16.39% becoming the new world leader in the industry until today. The relative importance of the main producer countries for the period between 1985 and 2010 can be seen in table 2.1.

Copper deposits are distributed throughout the world in a series of extensive and narrow metallurgical regions. Most of copper deposits are concentrated in the so-called "Ring of Fire" around the western coast of the Pacific Ocean in South and North America and in some copper belts located in eastern Europe and southern Asia. The geographical distribution of large and medium size copper deposits is shown in figure 2.3. As noted above, Chile is the major producer of copper and it accounts for 10 of the biggest 20 world copper mines, followed far behind by Indonesia, Peru and the United States with 2 world class mines each[5]. The biggest 10 mines in the world for the period between 1992 and 2010 are shown in table 2.2.

[5] Mines with a minimum production of at least 200 ktn. at any period of the sample.

Table 2.1: Producer Countries Market Shares (%) 1985 - 2010

Country[1]		**1985**	**1990**	**1995**	**2000**	**2005**	**2010**
1.	**Chile**	16	18	25	35	36	34
2.	**China**	3	3	4	4	5	8
3.	**Peru**	5	3	4	4	7	7
4.	**USA**	13	18	19	11	8	7
5.	**Indonesia**	1	2	5	8	7	5
6.	**Australia**	3	3	4	6	6	5
7.	**Zambia**	6	5	3	2	3	4
8.	**Russia**	0	0	5	4	4	4
9.	**Canada**	9	8	7	5	4	3
10.	**Congo DR**	6	4	0	0	0	3

Source: Codelco

Note (1): Ranking is based on output in 2010.

Figure 2.3: World Copper Mines 1992 - 2010

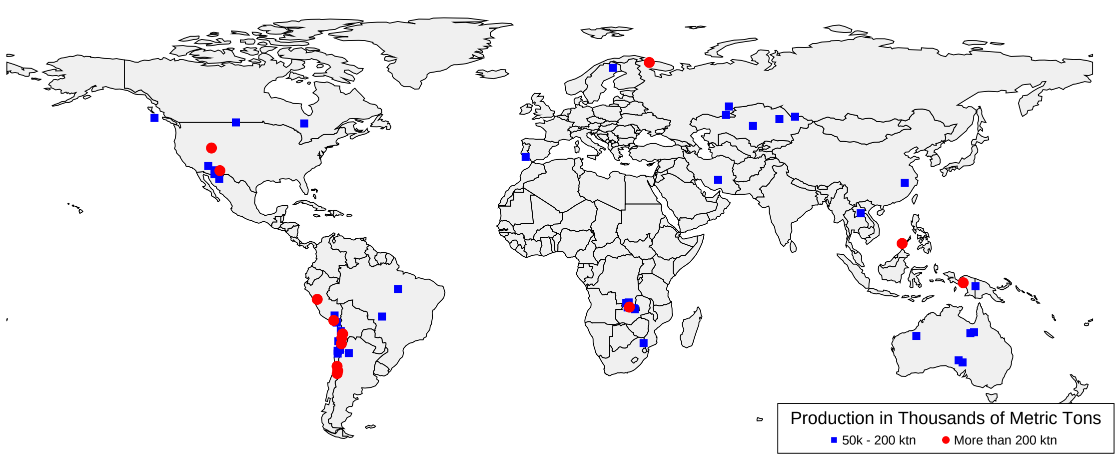


Table 2.2: The Biggest 10 Mines in the World 1992 - 2010

	Mine name[1]	**Country**	**Operator**	**Annual production (thousand Mt)**
1.	**Escondida**	Chile	BHP Billiton	1443.5
2.	**Grasberg**	Indonesia	Freeport McMoran	834.1
3.	**Chuquicamata**	Chile	Codelco	674.1
4.	**Collahuasi**	Chile	Xstrata Plc	517.4
5.	**Morenci**	USA	Freeport McMoran	500.9
6.	**El Teniente**	Chile	Codelco	433.7
7.	**Norilsk**	Russia	Norilsk Group	392.7
8.	**Los Pelambres**	Chile	Antofagasta Plc	379.0
9.	**Antamina**	Peru	BHP Billiton	370.2
10.	**Batu Hijau**	Indonesia	Newmont Mining	313.8

Source: Codelco.

Note (1) Ranking is based on maximum annual production during 1992-2010.

2.5 The Industry Today

Prices. Copper is a commodity traded at spot prices which are determined in international auction markets such as the London Metal Exchange (LME) and the New York Commodity Exchange (Comex).[6] However, from the end of the Second World War until the late 1970s, the international copper market was spatially segregated in two main markets: The U.S. local market and a market for the rest of the world. In the US market the price was set by the largest domestic producers. In contrast, in the rest of the world,

[6]A typical contract between producers and consumers specifies the frequency and point of deliveries. However, price is not specified in contracts, but is determined as the spot price in either COMEX or LME at the time of delivery.

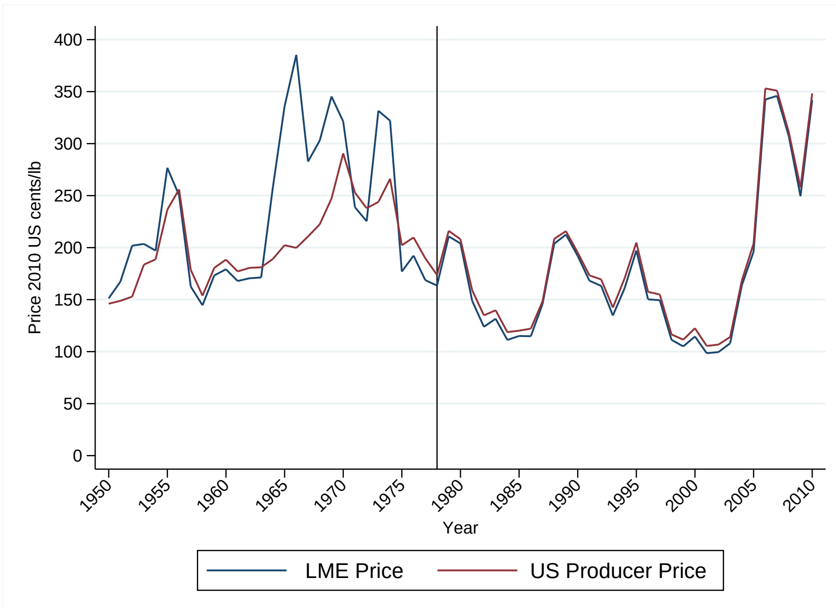
copper was sold at LME spot prices. This period, known as the “two-price system”, officially ended in 1978, when the largest US producers announced that they would use the Exchange prices as reference to set their contracts.

Figure 2.4 depicts both LME and US producer copper prices (in constant 2010 US dollars) from 1950 to 2010. A glance at this figure shows that prices present a slightly declining trend. However, it is possible to identify at least three major booms in this period. Radetzki (2006) states that the post war booms of the early 1950s, early 1970s and 2004 onwards can be explained by demand shocks. Furthermore, he explains that the first boom was caused by inventory build up in response to the Korean War, the second boom in turn was triggered by the price increases instituted by the oil cartel, while the third boom has been a consequence of the explosive growth of China’s and India’s row materials demand. In an attempt to give a deeper understanding of the current boom, Radetzki et al. (2008) state that increasing demand is not a full explanation for the high prices observed in the last period. Hence, they postulate three possible explanations for the 2004 onwards boom: firstly, it now takes much longer time to build new capacity than in previous booms. Secondly, investors could have failed to predict the increasing demand, underestimating needed capacity. Finally, exploring costs may have increased, pushing up in turn prices to justify investment in new capacity. However, there is very little econometric evidence that measures the contribution of each of these factors.

Consumption. Copper is the world’s third most widely used metal, after iron and aluminum. Its unique chemical and physical properties (e.g., excellent heat and electricity conductivity, corrosion resistance, non-magnetic and antibacterial) make it a very valuable production input in industries such as electrical and telecommunications, transportation, industrial machinery and construction, among others. Fueled by the strong economic development in East Asia, and specially in China, the consumption of copper has grown rapidly. In 2008, world copper consumption was approximately 15 million tonnes, grossing roughly $105 billion in sales. Table 2.3 shows the consumption shares of the top ten consumer countries starting in 1980[7]. In this period China began an economic reform process, where the market rather the state has driven the Chinese

[7]Ranking list is elaborated in base of the top ten consumer countries in 2009.

Figure 2.4: Copper Price 1950 - 2009



Source: U.S. Geological Survey.
Deflator: U.S. Consumer Price Index (CPI). 2010 = 100

economy, which has been very successful and it has led China to an important period of economic growth and industrial development. This China's economic success has permitted it to overcome the United States' consumption since 2002. Moreover, in the period of 2005 to 2009 China has almost tripled the U.S. consumption, accounting roughly for 28% of world copper consumption.

Table 2.3: World Consumption Shares (%) of Refined Copper 1980 - 2009

Country[1]		1980-84	1985-89	1990-94	1995-99	2000-04	2005-09
1.	**China**	5.92	6.09	7.19	10.07	17.32	28.00
2.	**USA**	20.63	20.43	20.9	21.07	16.34	11.59
3.	**Germany**	-	3.85	9.11	8.16	7.20	7.40
4.	**Japan**	13.59	12.49	13.48	10.49	7.89	6.62
5.	**South Korea**	1.51	2.41	3.54	4.73	5.71	4.59
6.	**Italy**	3.85	3.99	4.41	4.24	4.31	3.88
7.	**Russia**	-	2.86	3.69	1.24	2.33	3.39
8.	**Taiwan**	1.07	1.99	3.94	4.49	4.02	3.36
9.	**India**	0.90	1.14	1.06	1.62	1.93	2.73
10.	**France**	4.51	3.98	4.33	4.16	3.53	2.42

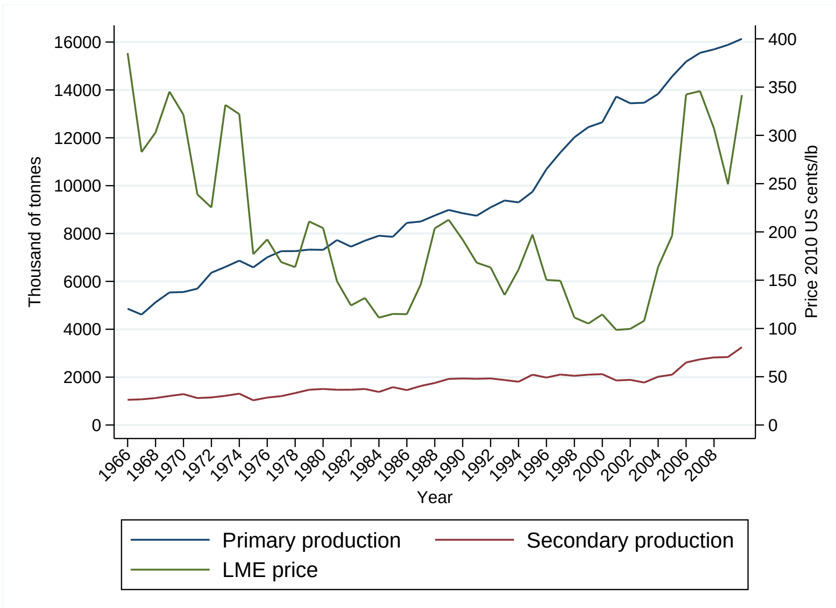
Source: ICSG

Note (1): Ranking is based of consumption in 2009.

Supply. The supply of refined copper originates from two sources, primary production (mine production) and secondary production (copper produced from recycling old scrap). As figure 2.5 shows primary production has almost tripled whereas secondary production has increased much more modestly. Some tentative explanations for this fact can be found in the existing literature of mineral economics. An important factor to explain this poor growth of the secondary production is that the cost of recycling copper scrap has remained high, especially when copper scrap is old (Gómez et al., 2007).

Other important factor is the effort of primary copper producers to reduce their production costs over this period that has contributed to a decline in the real price of copper since the early 1970s.

Figure 2.5: World Primary and Secondary Copper Production 1966 - 2009

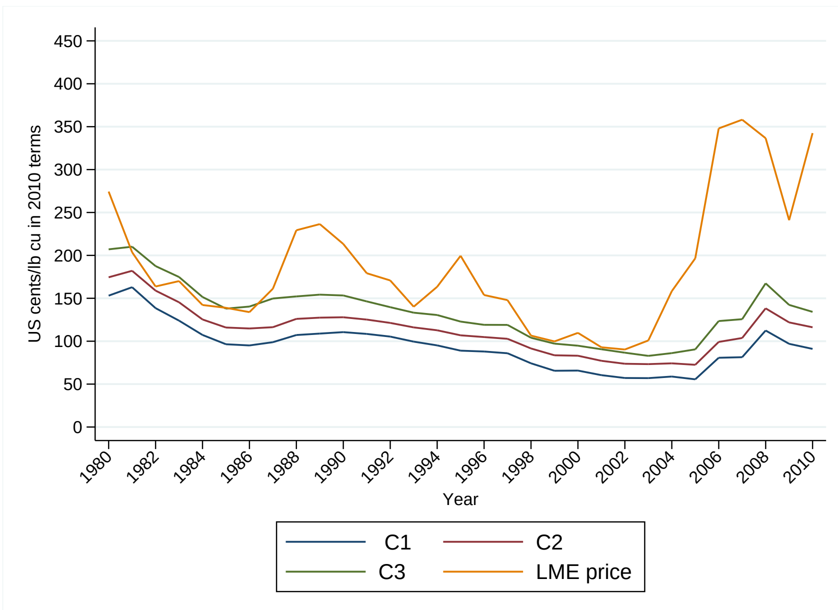


Source: ICSG

Copper costs have been extensively studied in the literature, e.g., Foley and Clark (1982), Davenport (2002), Crowson (2003, 2007) and Agostini (2006), as well as reports from companies and agencies. In mineral economics, costs are mainly classified in cash costs, operating costs and total costs. Cash costs (C1) represent all costs incurred at mine level, from mining through to recoverable copper delivered to market, less net by-product credits. Operating costs (C2) are the sum of cash costs (C1) and depreciation and amortization. Finally, total costs (C3) are operating costs (C2) plus corporate overheads, royalties, other indirect expenses and financial interest. Figure 2.6 shows world average copper costs and copper price in 2010 real terms from 1980 onwards. Both price and costs moved cyclically around a declining trend. However, since 2003 price has increased steadily while costs, with a certain lag, have increased since 2005. Part of the decrease in costs can be explained by management improvement

(Pérez, 2010), the introduction of SX-EW technology and geographical change in the production, from high-cost regions to low-cost regions Crowson (2003). The increase in costs in the last period can be explained by an increase in input prices and a decline in ore grades (Pérez, 2010).

Figure 2.6: World Average Copper Costs 1980 - 2010



Source: Brook Hunt.

Table 2.4 compares weighted average costs between top ten producer countries in the period from 1980 to 2010. Chile, Indonesia and Peru present the lowest costs for most of the period. Interestingly, USA has experienced the most dramatic decline in average costs. These three countries have become the most cost efficient places to produce copper.

Table 2.4: Weighted Average Costs by Country 1980-2010

Country$^{(1)(2)}$		**1980-84**	**1985-89**	**1990-94**	**1995-99**	**2000-04**	**2005-10**
1.	**Indonesia**	1.05	0.78	0.67	0.26	0.22	0.22
2.	**Peru**	1.21	1.16	1.05	0.74	0.54	0.40
3.	**USA**	1.72	1.15	1.03	0.86	0.74	0.71
4.	**Chile**	1.03	0.76	0.91	0.71	0.54	0.82
5.	**China**	-	-	-	0.72	0.79	1.02
6.	**Russia**	-	-	-	0.89	0.61	1.09
7.	**Australia**	1.59	1.04	1.00	0.89	0.64	1.26
8.	**Poland**	-	-	0.62	1.06	0.84	1.27
9.	**Canada**	1.35	1.10	1.23	0.96	0.77	1.34
10.	**Zambia**	1.52	0.82	0.89	1.16	1.02	1.54
	World Average	1.37	1.01	1.03	0.80	0.59	0.86

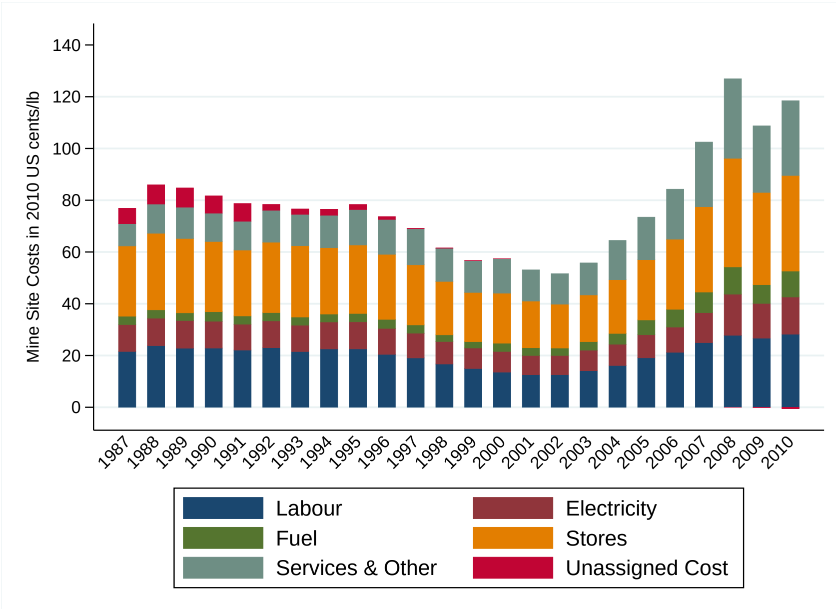
Source: Brook Hunt.

Note (1): Ranking is based on average costs in 2010.

Note (2): In US dollars per pound (Deflated 2010)

Figure 2.7 presents the main cost components of copper production, in constant (2010) US dollars. The biggest contributors to production costs are the storage costs, which accounted for roughly 33%, on average, during this period. Labor costs are the second most important component in production costs. Labor costs increased, in real terms, from 0.21 $/lb to 0.28 $/lb between 1987 and 2010, but this represented a reduction from 28% to 24% of total production costs, as other costs, such as fuel and services, experienced larger increases. Electricity, that is intensively used at the SX-EW and refining stages, represents on average roughly 13% of the production costs of a pound of copper.

Figure 2.7: Average Cost by Component 1987 - 2010



Source: Brook Hunt.

3

A Microeconometric Theoretical Model for the Copper Mining Industry

This chapter has been co-authored with Dr. Victor Aguirregabiria, Professor in Economics, Department of Economics, University of Toronto, Max Gluskin House, Toronto, Ontario, M5S 3G7, Canada. Email: victor.aguirregabiria@utoronto.ca

This chapter builds upon the natural resources literature. Natural resource industries have been little explored in the modern Industrial Organization literature. Most of the research had focused in commodity price fluctuations and the Hotelling's rule, and cartel behavior. New tools in empirical industrial organization and new and better data sets developed in recent years are leading to a revival of the interest on these old and somewhat forgotten models of natural resources. For instance, Slade (2013a) explores investment decisions under uncertainty in the U.S. copper industry. Lin (2013) estimates a dynamic game of investment in the offshore petroleum industry. Huang and Smith (2014) estimate a dynamic entry game of a fishery resource.

The dynamics of the extraction of natural resources has been analyzed by economists since Hotelling's seminal paper. The basic and well known Hotelling model considers the extraction path that maximizes the expected and discounted flow of profits of a firm given a known and finite stock of reserves of a nonrenewable resource. An important prediction of the model is that, under the optimal depletion of the natural resource, the price-cost margin should increase at a rate equal to the interest rate, i.e., Hotelling rule. Hotelling's paper also first introduced the concept of depletion effect which reflects the increasing cost associated with the scarcity of the resource.

Subsequent literature on natural resources has extended Hotelling model in different directions. Pindyck (1978) includes exploration in Hotelling model, and uses this model to derive the optimal production and exploration paths in the competitive and monopoly cases. He finds that the optimal path for price is U-shaped. Gilbert (1979) and Pindyck (1980) introduce uncertainty in reserves and demand. There has been also substantial amount of empirical work testing Hotelling rule. Most empirical studies have found evidence that contradicts Hotelling's rule. Farrow (1985) and Young (1992), using a sample of copper mines, reject the Hotelling rule. In contrast, Slade and Thille (1997) finds a negative and significant depletion effect and results more consistent with theory using a model of pricing of a natural-resource that integrates financial and output information. Krautkraemer (1998) and Slade and Thille (2009) provide comprehensive reviews of the theoretical and empirical literature, respectively, extending Hotelling model.

The copper industry has been largely examined by empirical researches since the well known study of competition by Herfindahl in 1956. In general, the literature on the copper industry can be divided into four groups according to their main interest. Most of these studies have used this industry to test more general theories on prices, uncertainty, tax effects and efficiency.

A first group include those studies in which the main purpose is to examine the behavior of prices and investment under uncertainty in the industry. A seminal paper in this branch is the work by Fisher et al. (1972a) who uses aggregate yearly data on prices, output and market characteristics for the period 1948-1956 and several countries to estimate the effect on the LME copper price of an exogenous increase in supply either from new local policies or new discovery. They found that these increases in supply will be mainly absorbed by offsetting reductions in the supply from other countries. Harchaoui and Lasserre (2001) study capacity decisions of Canadian copper mines during 1954-1980 using a dynamic investment model under uncertainty. They found that the model explains satisfactorily the investment behavior of mines. Slade (2001) estimates a real-option model to evaluate the managerial decision of whether to operate a mine or not also using a sample of Canadian copper mines. More recently, Slade (2013a) investigates the relationship between uncertainty and investment using a extensive data series of investment decisions of U.S. copper mines. She uses a reduced form analysis to estimate the investment timing to go forward and the price thresholds that trigger this decision. Interestingly, she finds that with time-to-build, the effect of uncertainty on investment is positive. In a companion paper, Slade (2013b) studies the main determinants of entry decisions using a reduced form analysis. She extends the previous analysis adding concentration of the industry and resource depletion. Here, copper is considered as a common pool resource and depletion is measured as cumulative production in all the industry rather than depletion at single mine level. Slade finds that technological change and concentration of the industry has a positive effect on entry decisions whereas resource depletion affects negatively the new entry of mines. Interestingly, in contrast to the companion paper, Slade finds a negative effect of uncertainty on entry decisions. The provided explanation is that an increase in uncertainty (with time-to-build) may encourage the implementation of investment projects that are at the planning stage, but it has also a negative effect in the long-run by moving resources towards industries with lower levels of uncertainty.

A second group of papers have studied the conditions for dynamic efficiency in mines output decisions in the spirit of the aforementioned Hotelling's model. Most of these studies use a structural model where the decision variable is the amount of output. Young (1992) examines Hotelling's model using a panel of small Canadian copper mines for the period 1954-1986. She estimated the optimal output path in a two stage procedure. In a first step, she estimates a translog cost function, and in a second step the estimated marginal cost is plugged into the Euler equation of the firm's intertemporal decision problem for output, and the moment conditions are tested in the spirit of the GMM approach in Hansen and Singleton (1982). The results showed that her data is no consistent with Hotelling model. Slade and Thille (1997) use the same data as in Young (1992) to analyze the expected rate of return of a mine investment by combining Hotelling model with a CAPM portfolio choice model. Gaudet (2007) explores copper price behavior and survey the factors that characterize the rate of return on holding an exhaustible natural resource stock and determine their implications in the context of the Hotelling's model.

A third group of papers study the effects of taxes and / or environmental policies (certifications) on the decisions of copper mines. Slade (1984) studies the effect of taxes on the decision of ore extraction and metal output. Foley and Clark (1982) evaluates the effects of potential state taxes on price and production in 47 U.S. copper mines using proprietary cost data for the period 1970-1978. Tole and Koop (2013) studies the implications on costs and operation output decisions of the adoption of environmental ISO using a panel of 99 copper mines from different producing countries for the period 1992-2007. They find evidence that ISO adoption increases costs.

This model and its empirical results emphasize the importance of the extensive margin, and the heterogeneity and endogeneity of ore grade to explain the joint dynamics of supply and prices in the copper industry. Krautkraemer (1988, 1989) and Farrow and Krautkraemer (1989) present seminal theoretical models on these topics.

Finally, a reduced group of papers has studied the competition and strategic interactions in the copper industry. Agostini (2006) estimates a static demand and supply and a conjectural variation approach *a la* Porter (1983) to measure the nature or degree of competition in the U.S. copper industry before 1978. He finds evidence consistent with competitive behavior.

3.1 Basic Framework

A copper firm, indexed by f, consists of a set of mines $\mathcal{M}_f$, indexed by $i \in \mathcal{M}_f$ each one having its own specific characteristics. Time is discrete and indexed by t. A firm's profit at period t is the sum of profits from each of its mines, $\Pi_{ft} = \sum_{i \in \mathcal{M}_f} \pi_{it}$. For the moment, we assume that profits are separable across mines and we focus on the decision problem of a single mine. Every period (year) t, the managers of the mine make two decisions that have implications on current and future profits: (1) whether to be active or not next period ($a_{it+1} \in \{0, 1\}$); and (2) how much output to produce (q_{it}). Let $\mathbf{d}_{it} \equiv (a_{it+1}, q_{it})$ be the vector with these decision variables, and let $\mathbf{y}_{it} \equiv (a_{it}, k_{it}, g_{it}, r_{it})$ be the vector of endogenous state variables, where k_{it} represents capital equipment, r_{it} represents ore reserves, and g_{it} is ore grade. Similarly, let $(\mathbf{z}_{it}, \varepsilon_{it})$ be the vector with all the exogenous state variables in demand, productivity, and input prices, where $\mathbf{z}_{it}$ represents exogenous state variables that are observable to the researcher, and ε_{it} represents unobservables. We use $\mathbf{x}_{it} \equiv (\mathbf{y}_{it}, \mathbf{z}_{it})$ to represent the vector with all the observable state variables, and $\mathbf{s}_{it} \equiv (\mathbf{x}_{it}, \varepsilon_{it})$ to represent all the state variables. Then, the dynamic decision problem of a mine manager can be represented using the Bellman equation:

$$\begin{aligned} V_i\left(\mathbf{s}_{it}\right) \quad = \quad & \max_{\mathbf{d}_{it}} \Big\{ \pi_i\left(\mathbf{d}_{it}, \mathbf{s}_{it}\right) \\ & + \beta \int V_i\left(\mathbf{y}_{it+1}, \mathbf{z}_{it+1}, \varepsilon_{it+1}\right) \; f_y(\mathbf{y}_{it+1} | \mathbf{d}_{it}, \mathbf{y}_{it}) \; f_z(\mathbf{z}_{it+1} | \mathbf{z}_{it}) \; f_\varepsilon(\varepsilon_{it+1} | \varepsilon_{it}) \Big\} \end{aligned} \tag{3.1.1}$$

where $\beta \in (0, 1)$ is the discount factor, and f_y, f_z, and f_ε are the transition probability functions of the state variables.

The rest of this section describes in detail the economics of the primitive functions π_i, f_y, f_z, and f_ε. Section 3.2 presents the parametric specification of these functions.

(a) Profit function. The one-period profit function of a mine is:

$$\pi_{it} = P_t \, q_{it} - VC_{it}(q_{it}) - FC_{it} - EC_{it} - XC_{it} \tag{3.1.2}$$

where P_t is the price of copper in the international market, VC_{it} is the variable cost function, FC_{it} represents fixed operating costs, EC_{it} is the cost of entry (re-opening) and XC_{it} is the cost of closing the mine.

(b) Markets, competition, and demand function. The market of copper is global and its price P_t is determined by aggregate world demand and supply. World inverse demand function is:

$$P_t = p\left(Q_t, \mathbf{z}_t^{(d)}, \varepsilon_t^{(d)}\right) \tag{3.1.3}$$

where Q_t is the aggregate industry output at period t, and $\left(\mathbf{z}_t^{(d)}, \varepsilon_t^{(d)}\right)$ are exogenous variables that enter in the demand function. $\mathbf{z}_t^{(d)}$ is a vector of exogenous demand shifters observable to the researcher, such as GDP growths of US, EU, and China, and the price of aluminium (i.e., the closest substitute of copper). $\varepsilon_t^{(d)}$ is a demand shock that is unobservable to the researcher. We assume that firms (mines) in this industry compete a la Nash-Cournot. When a mine decides its optimal amount of output at period t, q_{it}, it takes as given the output choices of the rest of the mines in the industry, Q_{-it}. Note that our game of Cournot competition is dynamic. As we describe below, a mine output decision has effects on future profits. Mine managers are forward looking and take into account these dynamic effects. We assume that mines are price takers in input markets.

(c) Active / no active choice. Every year t, the managers of a mine decide whether to operate the mine next period or not. We represent this decision using the binary variable $a_{it+1} \in \{0, 1\}$, where $a_{it+1} = 1$ indicates that the mine decides to be active (operating) at period $t + 1$. Based on information from conversations with industry experts, we assume that there is time-to-build in the decision of opening or closing a mine: a decision taken at year t is not effective until year $t + 1$. Our conversations with industry experts also indicate that almost all the mine closings during our sample period were not permanent closings. This is reinforced by evidence in our data showing a

substantial amount of reopenings during our sample period. Therefore, in our model, we consider that mine closings are reversible decisions. Though re-opening is reversible, it is costly. If the mine is not active at t, there is a fix cost EC_{it} of starting-up at $t+1$. This cost may depend on state variables such as mine size as measured by reserves, and the price of fixed inputs. Closing a mine is costly too. If the mine is active at year t and the managers decide to stop operations at $t+1$, there is a cost of closing the mine. Start-up and closing costs are paid at period t but the decision is not effective until $t+1$. Start-up cost has the following form:

$$EC_{it} = c_i^{(e)}(\mathbf{x}_{it}) + \varepsilon_{it}^{(e)}, \tag{3.1.4}$$

and similarly, the closing cost is:

$$XC_{it} = c_i^{(x)}(\mathbf{x}_{it}) + \varepsilon_{it}^{(x)}, \tag{3.1.5}$$

where $c_i^{(e)}(.)$ and $c_i^{(x)}(.)$ are functions of the vector of observable state variables $\mathbf{x}_{it}$ that we specify below. $\varepsilon_{it}^{(e)}$ and $\varepsilon_{it}^{(x)}$ are state variables that are observable to mine managers but unobservable to the researcher.

(d) Production decision / Production function / Variable costs. An active mine at year t (i.e., $a_{it} = 1$) should decide how much copper to produce during the year, q_{it}. This is a dynamic decision because current production has two important implications on future profits. First, current production depletes reserves and then reduces the expected lifetime of the mine. Reducing reserves can also increase future production costs. A second dynamic effect is that the depletion of the mine has a negative impact on ore grade. We capture these effects through the specification of the variable cost function (or equivalently, the production function), and through the transition rule of ore grade. The production function of copper in a mine is Cobb-Douglas with six different production inputs:

$$q_{it} = (\ell_{it})^{\alpha_\ell} \;\; (e_{it})^{\alpha_e} \;\; (f_{it})^{\alpha_f} \;\; (k_{it})^{\alpha_k} \;\; (r_{it})^{\alpha_r} \;\; (g_{it})^{\alpha_g} \;\; \exp\{\omega_{it}\} \tag{3.1.6}$$

where ℓ_{it} is labor, e_{it} and f_{it} represent electricity and fuel, respectively, k_{it} is capital equipment, r_{it} represents ore reserves, g_{it} is ore grade, ω_{it} is a productivity shock, and α's are parameters. Capital, reserves, ore grade, and productivity shock, $(k_{it}, r_{it}, g_{it}, \omega_{it})$, are predetermined variables for the output decision at year t. The mine chooses the amount of labor, electricity, and fuel at year t, $(\ell_{it}, e_{it}, f_{it})$, and this decision is equivalent to the choice of output q_{it}. The first order conditions of optimality for the three variable inputs are the following: for every variable input $v \in \{\ell, e, f\}$:

$$MR_{it} \frac{\partial q_{it}}{\partial v_{it}} - p^v_{it} + \beta\, \mathbb{E}_t \left[\frac{\partial V_{it+1}}{\partial \mathbf{y}_{it+1}} \frac{\partial \mathbf{y}_{it+1}}{\partial q_{it}} \right] \frac{\partial q_{it}}{\partial v_{it}} \quad = \quad 0 \tag{3.1.7}$$

where: $MR_{it} \equiv [p'_t(Q_t)\, q_{it} + P_t]$ is the marginal revenue of mine i; $\partial q_{it}/\partial v_{it}$ is the marginal productivity of variable input $v \in \{\ell, e, f\}$; p^v_{it} is the price of this input at the input markets where mine i operates; $\partial \mathbf{y}_{it+1}/\partial q_{it}$ represents the dynamic effects of current output on next period reserves and ore grade, that we describe below; and $\partial V_{it+1}/\partial \mathbf{y}_{it+1}$ is the marginal value of reserves and ore grade. Though the choice of these variable inputs have dynamic implications, the dynamic effect operates only through current output. Therefore, it is clear that these dynamic marginal conditions of optimality imply the standard static condition that the ratio between marginal productivity of inputs should equal the ratio between input prices:

$$\frac{\partial q_{it}/\partial \ell_{it}}{\partial q_{it}/\partial e_{it}} = \frac{p^\ell_{it}}{p^e_{it}} \quad \text{and} \quad \frac{\partial q_{it}/\partial \ell_{it}}{\partial q_{it}/\partial f_{it}} = \frac{p^\ell_{it}}{p^f_{it}} \tag{3.1.8}$$

Using these conditions, the production function, and the definition of variable cost as $VC_{it} \equiv p^\ell_{it}\, \ell_{it} + p^e_{it}\, e_{it} + p^f_{it}\, f_{it}$, we can derive the variable cost function[1]:

$$VC_{it} = \alpha_v \left[\frac{\left(p^\ell_{it}/\alpha_\ell\right)^{\alpha_\ell} \ \left(p^e_{it}/\alpha_e\right)^{\alpha_e} \ \left(p^f_{it}/\alpha_f\right)^{\alpha_f}}{(k_{it})^{\alpha_k}\ (r_{it})^{\alpha_r}\ (g_{it})^{\alpha_g}\ \exp\{\omega_{it}\}}\ q_{it} \right]^{(1/\alpha_v)} \tag{3.1.9}$$

where α_v is the sum of the coefficients of all the variable inputs, i.e., $\alpha_\ell + \alpha_e + \alpha_f$. The

[1] See Appendix A.1 for a more detailed derivation of the variable and marginal costs.

marginal cost is equal to $MC_{it} = (1/\alpha_v)\,(VC_{it}/q_{it})$.

(e) Transition rule for reserves and ore grade. The endogenous evolution of ore reserves is described by the equation:

$$r_{i,t+1} = r_{it} - \left(\frac{q_{it}}{g_{it}}\right) + z^{(r)}_{i,t+1} \tag{3.1.10}$$

q_{it}/g_{it} represents the amount of ore that was extracted from the mine at period t to produce q_{it} units of copper. $z^{(r)}_{i,t+1}$ is an stochastic shock that represents updates in ore reserves due to new discoveries or reviews in the estimated value of reserves. For the moment, we assume that $z^{(r)}_{i,t+1}$ follows an exogenous stochastic process. More specifically, $z^{(r)}_{i,t+1}$ follows a first order Markov process, i.e., new discoveries have positive serial correlation. We assume that $z^{(r)}_{i,t+1}$ is unknown to the mine managers when they make their decisions at year t, but they know z^{r}_{it}, and this is a state variable of the model. Note that $z^{(r)}_{it}$ is observable to the researcher, i.e., for every mine i and year t, we can construct $z^{(r)}_{it} = r_{it} - r_{it-1} + q_{it-1}/g_{it-1}$. For periods where a mine is not active, we have that $z^{(r)}_{it} = 0$.

The transition for ore grade captures the depletion effect on the quality of the mine. Following Caldentey et al. (2006) and consistent with mining practices, we assume that a mine is divided into a collection of blocks each one having particular geological characteristics, i.e., its own ore grades and extraction costs. These blocks represent minimal extraction units so that the miner's production decisions are made at block level. Usually, blocks with the highest ore grade are extracted first which determine the block extraction path of the mine. As deposits are depleted, mining shifts to blocks with the next best quality. However, given the physical characteristics of the mine, factors other than ore grade, such as the depth level of the block, hardness of the rocks, and distance to the processing plant, play also a role in the optimal path of block extraction. We have tried different specifications for the transition rule of ore grade. The following equation describes our favored specification:

$$\ln g_{i,t+1} = \ln g_{it} - \delta^{(g)}_q \, \ln(1 + q_{it}) + \delta^{(g)}_z z^{(r)}_{it} + \varepsilon^{(g)}_{it+1} \tag{3.1.11}$$

The model imposes the restriction that all the effects, exogenous or endogenous, on ore grade are permanent. We have tried specifications where the parameter of g_{it} is smaller than 1, and the estimate of this parameter, though precise, is not significantly different to 1. The parameter $\delta_q^{(g)}$ (depletion elasticity of ore grade) is positive and $-\delta_q^{(g)} \ln q_{it}$ captures the depletion effect on ore grade. The term $\delta_z^{(g)}\ z_{it}^{(r)}$ takes into account that new discoveries may imply changes in ore grade.

(f) Fixed costs. The operation of a copper mine is very intensive in specialized and expensive capital equipment, i.e., extraction machinery, transportation equipment, and processing/refining equipment. These inputs are typically fixed within a year, but they imply costs of amortization, leasing, and maintenance. These costs depend on the size of the mine as measured by reserves and capital.

$$FC_{it} = p_{it}^k\ k_{it} + \theta_1^{(fc)}\ k_{it} + \theta_2^{(fc)}\ r_{it} + \theta_3^{(fc)}\ (k_{it})^2 + \theta_4^{(fc)}\ (r_{it})^2, \qquad (3.1.12)$$

where p_{it}^k price of capital, as measured by interest costs, and $\{\theta_j^{(fc)}\}$ are parameters that capture the relationship between mine size and fixed costs. Parameters $\theta_3^{(fc)}$ and $\theta_4^{(fc)}$ can be either positive or negative, depending on whether there are economies or diseconomies of scale associated to the size of the mine (in contrast to the more standard economies of scale associated to the level of output, that are captured by the fixed cost itself).

3.2 Euler Equations

In this section, we derive the dynamic conditions of optimality that we use for the estimation of model parameters and for testing some specification assumptions. These optimality conditions, that we generally describe as Euler equations, involve decisions and state variables, at a small number of consecutive years. We derive two different types of Euler equations: (a) for output when output is positive; and (b) for the binary choice of being active or not. Euler equation (a) is standard and it can be derived by combining marginal conditions of optimality at two consecutive periods with the application of the Envelope Theorem in the Bellman equation. The second Euler equation is not standard. The Euler equation for the entry decision is not standard because it involves discrete choices and, in principle, these choices do not involve marginal conditions of optimality. Following Aguirregabiria and Magesan (2013), we show that our dynamic decision model has a representation where discrete choices for output is described in terms of Conditional Choice Probabilities (CCPs). Then, we show that a mine optimal decision rule for this discrete decisions implies marginal conditions of optimality. Finally, we show that we can combine these marginal conditions at two consecutive periods to derive Euler equations.

For notational simplicity, in this section we omit the mine subindex i.

3.2.1 Euler Equation for Output

Consider a mine that is active at two consecutive years, t and $t+1$. Note that the time-to-build assumption, on opening and closing decisions, implies that when the managers of the mine make output decision at year t they know that the mine will be active at year $t+1$ with probability one. The managers know that the marginal condition of optimality with respect to output will hold at period $t+1$ with probability one. Under this condition and taking into account the form of the profit function π_t, we can derive a standard Euler equation for output. We show in Appendix A.2 that the Euler equation for output is:

$$MR_t - MC_t = \beta \, \mathbb{E}_t \left([MR_{t+1} - MC_{t+1}] \, \frac{(1+q_{t+1})}{(1+q_t)} + \alpha_g \delta_q^{(g)} \frac{q_{t+1}}{(1+q_t)} MC_{t+1} \right) \tag{3.2.1}$$

where $\alpha_g \delta_q^{(g)} \dfrac{q_{t+1}}{(1+q_t)} MC_{t+1}$ represents the increase in marginal costs due to the depletion effect. This Euler equation already contains several extensions with respect to Hotelling's rule. In a simple dynamic decision model for the exploitation of a nonrenewable resource, where firms do not have market power, the marginal production cost does not depend on reserves and ore grade and $\left(\frac{1+q_{t+1}}{1+q_t}\right) = 1$, the Euler equation of the model becomes $P_t - MC_t = \beta \, \mathbb{E}_t \left(P_{t+1} - MC_{t+1}\right)$, that often is represented as

Hotelling's rule as:

$$\frac{\mathbb{E}_t\left(P_{t+1} - MC_{t+1}\right)}{P_t - MC_t} - 1 = \frac{1-\beta}{\beta} \tag{3.2.2}$$

This equation is a particular solution of our model and implies that, on average, the price-cost margin increases over time at an annual rate equal to $(1 - \beta)/\beta$, e.g., for $\beta = 0.95$, this rate is equal to 5.2%. This prediction is typically rejected for most non-renewable resources, and for copper in particular. The Euler equation in (3.2.1) introduces two extensions that modify this prediction. First, a unit increase in output at period t implies an increase in the marginal cost at $t+1$ equal to $\alpha_g \delta_q^{(g)} \frac{q_{t+1}}{(1+q_t)} MC_{t+1}$. Depletion increases future marginal cost. This effect may offset, partly or even completely, the standard depletion effect on price-cost margin in Hotelling model. To see this, we can write the Euler equation as:

$$\frac{\mathbb{E}_t\left(P_{t+1} - MC_{t+1}\right)}{P_t - MC_t} - 1 = \frac{1-\beta}{\beta} - \frac{\mathbb{E}_t\left(\alpha_g \delta_q^{(g)} \frac{q_{t+1}}{(1+q_t)} MC_{t+1}\right)}{P_t - MC_t} \tag{3.2.3}$$

The second term in the equation is negative and it can be larger, in absolute, than $(1 - \beta)/\beta$. In chapter 6, we present our estimates of production function parameters and show that α_g is relatively large, i.e., point estimates between 0.59 and 0.77, depending on the estimation method.

3.2.2 Euler Equation for Discrete Choice Active/Non active

Let $\pi^*(a_{t+1}, \mathbf{x}_t) + \varepsilon_t(a_{t+1})$ be the one-period profit function such that: (a) it is conditional to the hypothetical choice of a_{t+1} for the active/no active decision; and (b) we have already solved in this function the optimal decision for output. By definition, we have that $\varepsilon_t(0) = -a_t \, \varepsilon_t^{(x)}$ and $\varepsilon_t(1) = -(1-a_t) \, \varepsilon_t^{(e)}$, and:

$$\pi^*(a_{t+1}, \mathbf{x}_t) \;=\; \pi\left(a_{t+1}, q^*[\mathbf{x}_t], \mathbf{x}_t\right) = \begin{cases} \Pi^*(\mathbf{x}_t) - a_t \, c_i^{(x)}(\mathbf{x}_t) & \text{if} \quad a_{t+1} = 0 \\ \\ \Pi^*(\mathbf{x}_t) - (1-a_t) \, c_i^{(e)}(\mathbf{x}_t) & \text{if} \quad a_{t+1} = 1 \end{cases} \tag{3.2.4}$$

where $\Pi^*(\mathbf{x}_t) \equiv VP^*(\mathbf{x}_t) - FC(\mathbf{x}_t)$ is the part of the profit function that does not depend on a_{t+1}. We can use the profit function to define a dynamic binary choice model that represents the part of our model related to the mine decision to be active or not. The Bellman equation of this problem is:

$$\begin{aligned} V\left(\mathbf{x}_t, \varepsilon_t\right) \;=\; & \max_{a_{t+1} \in \{0,1\}} \Big\{ \pi^*(a_{t+1}, \mathbf{x}_t) + \varepsilon_t(a_{t+1}) \\ & + \beta \int V(\mathbf{x}_{t+1}, \varepsilon_{t+1}) \; f_x^*(\mathbf{x}_{t+1} | a_{t+1}, \mathbf{x}_t) \; f_\varepsilon(\varepsilon_{t+1} | \varepsilon_t) \Big\} \end{aligned} \tag{3.2.5}$$

Let $a_{t+1} = \alpha^*(\mathbf{x}_t, \varepsilon_t)$ be the optimal decision rule of this DP problem. Under the assumption that $\varepsilon_t = \{\varepsilon_t(0), \varepsilon_t(1)\}$ is i.i.d. over time, this optimal decision rule has a threshold structure, i.e., there is a real-valued function $\mu^*(\mathbf{x}_t)$ such that:

$$a_{t+1} = \alpha^*(\mathbf{x}_t, \varepsilon_t) = 1\left\{\varepsilon_t(0) - \varepsilon_t(1) \leq \mu^*(\mathbf{x}_t)\right\} \tag{3.2.6}$$

Therefore, to characterize this optimal decision rule, we can concentrate in the class of decision rules with the structure $\alpha(\mathbf{x}_t, \varepsilon_t) = 1\left\{\varepsilon_t(0) - \varepsilon_t(1) \leq \mu(\mathbf{x}_t)\right\}$, for arbitrary $\mu(\mathbf{x}_t)$. Given the CDF of $\varepsilon_t(0) - \varepsilon_t(1)$, i.e., $F(.)$, and an arbitrary real-valued function $\mu(\mathbf{x}_t)$, we can uniquely define a Conditional Choice Probability (CCP) function:

$$P(\mathbf{x}_t) \equiv F\left(\mu(\mathbf{x}_t)\right) \tag{3.2.7}$$

This CCP function represents the probability of being active at period $t+1$ given the observable state $\mathbf{x}_t$ and given the decision rule μ.

It is clear that there is a one-to-one relationship between the three representations of a decision rule: (1) the representation in action space, $\alpha(\mathbf{x}_t, \varepsilon_t)$; (2) the threshold function $\mu(\mathbf{x}_t)$; and (3) the CCP function $P(\mathbf{x}_t)$. Following Aguirregabiria and Magesan (2013), we consider a representation of the model in terms of the CCP function. This representation has the following (integrated) Bellman equation:

$$V^P(\mathbf{x}_t) = \max_{P(\mathbf{x}_t)\in[0,1]} \left\{ \Pi^P(P(\mathbf{x}_t), \mathbf{x}_t) + \beta \int V^P(\mathbf{x}_{t+1})\, f_x^P(\mathbf{x}_{t+1}|P(\mathbf{x}_t), \mathbf{x}_t)\, d\mathbf{x}_{t+1} \right\} \tag{3.2.8}$$

with:

$$\Pi^P(P(\mathbf{x}_t), \mathbf{x}_t) \equiv (1 - P(\mathbf{x}_t))\, [\pi^*(0, \mathbf{x}_t) + e(0, \mathbf{x}_t, P)] + P(\mathbf{x}_t)\, [\pi^*(1, \mathbf{x}_t) + e(1, \mathbf{x}_t, P)], \tag{3.2.9}$$

where $e(a, \mathbf{x}_t, P)$ is the expected value of $\varepsilon_t(a)$ conditional on alternative a being chosen under decision rule $P(\mathbf{x}_t)$; and

$$f_x^P(\mathbf{x}_{t+1}|P(\mathbf{x}_t), \mathbf{x}_t) \equiv (1 - P(\mathbf{x}_t))\, f_x^P(\mathbf{x}_{t+1}|0, \mathbf{x}_t) + P(\mathbf{x}_t)\, f_x^P(\mathbf{x}_{t+1}|1, \mathbf{x}_t). \tag{3.2.10}$$

Proposition 2(i) in Aguirregabiria and Magesan (2013) shows that the optimal CCP function $P^*(\mathbf{x}_t)$ that solves Bellman equation (3.2.8) is the CCP function that corresponds to the optimal decision rule in our original problem in equation (3.2.5), i.e., $a_{t+1} = \alpha^*(\mathbf{x}_t, \varepsilon_t) = 1\,\{\varepsilon_t(0) - \varepsilon_t(1) \leq F^{-1}[P(\mathbf{x}_t)]\}$.

Using this representation property of our dynamic binary choice model, we can derive the following Euler equation that involves CCPs at periods t and $t+1$. We provide the details of this derivation in Appendix A.3.

$$\left[\frac{\pi^*(a_{t+1} = 1, \mathbf{x}_t) - \pi^*(a_{t+1} = 0, \mathbf{x}_t)}{\sigma_\varepsilon} - \ln\left(\frac{P(\mathbf{x}_t)}{1 - P(\mathbf{x}_t)} \right) \right]$$

$$+\beta\, \mathbb{E}_t \left[\frac{\pi^*(a_{t+2} = 1, a_{t+1} = 1, \mathbf{x}_{t+1}) - \pi^*(a_{t+2} = 1, a_{t+1} = 0, \mathbf{x}_{t+1})}{\sigma_\varepsilon} - \ln\left(\frac{P(a_{t+1} = 1, \mathbf{x}_{t+1})}{P(a_{t+1} = 0, \mathbf{x}_{t+1})} \right) \right] = 0 \tag{3.2.11}$$

Or taking into account the form of the profit function π_t:

$$\left[\frac{a_t\, c^{(x)}(\mathbf{x}_t) + (1-a_t)c^{(e)}(\mathbf{x}_t)}{\sigma_\varepsilon} - \ln\left(\frac{P(\mathbf{x}_t)}{1-P(\mathbf{x}_t)}\right)\right] \quad +$$

$$\beta\, \mathbb{E}_t \left[\frac{\Pi^*(\mathbf{x}_{t+1}) + c^{(e)}(\mathbf{x}_{t+1})}{\sigma_\varepsilon} - \ln\left(\frac{P(a_{t+1}=1, \mathbf{x}_{t+1})}{P(a_{t+1}=0, \mathbf{x}_{t+1})}\right)\right] \quad = \quad 0$$

4

Data and Descriptive Evidence

4.1 Data Description

We have built a unique dataset of almost two decades for this industry. We have collected yearly data for 330 copper mines from 1992 to 2010 using different sources. The dataset contains detailed information at the mine-year level on extraction of ore and final production of copper and by-products (all in physical units),[1] reserves, ore and mill grades, recuperation rate, capacity, labor, energy and fuel consumption (in physical units), input prices, total production costs, indicators for whether the mine is temporarily or permanently inactive, and mine ownership.[2] Mine level data is compiled for active mines by Codelco. This data set represents, approximately, 85% of the industry output.

[1]By-products include cobalt, gold, lead, molybdenum, nickel, silver, and zinc.

[2]We are especially grateful to Juan Cristobal Ciudad and Claudio Valencia of Codelco, Daniel Elstein of USGS, Carlos Risopatron and Joe Pickard of ICGS, and Victor Garay of Cochilco for providing the data for this analysis.

Price at the LME is collected by USGS. Capacity and consumption data are from ICSG.

Table 4.1 presents the summary statistics for variables both at the mine level and market level. On average, there are 172 active mines per year, with a minimum of 144 in year 1993 and a maximum of 226 in 2010. We describe the evolution of the number of mines, entry, and exit in section 4.2 below. On average, an active mine produces 64 thousand tonnes of copper per year. The average copper concentration or grade is 1.21%. There is large heterogeneity across mines in production, capacity, reserves, ore grade, and costs. We describe this heterogeneity in more detail in section 4.2.

Next, we describe the main variables in the data set:

Market Level:

LME price: Copper price at the London Metal Exchange in US$ per tonne (USGS).

World Consumption: World total consumption of primary copper in thousands of tonnes (ICSG).

World Capacity: World annual production capability for copper units, whether contained in concentrate, anode, blister, or refined copper in thousands of metric tonnes (ICSG).

World Production: World total mine copper produced by mines in thousands of tonnes (USGS).

Mine Level:

Number of Mines: Number of active mines per year (Codelco).

Capacity: Capacity reflects a plant's annual production capability for copper units, whether contained in concentrate, anode, blister, or refined copper in thousands of metric tonnes. Capacity is usually determined by a combination of engineering factors, such as gross tonnage of milling capacity and feed grades that determine long-term sustainable production rates. Mine capacity is not generally adjusted to reflect short-term variations in ore grade but would reflect long-term trends in ore grade. Electrowinning capacity is usually determined by tankhouse parameters. (ICGS)

Copper production: Total payable copper produced either by concentrates or electrowinning in thousands of tonnes. Production data in concentrates is presented in terms of the amount of metal contained in the concentrate (Codelco).

By-products production: A mine can extract by-products or secondary metals as consequence of copper mining, this by-products can include cobalt, gold, lead, molybdenum, nickel, silver, and zinc (Codelco). Which by-product is extracted at each mine depends on the geographical location of the mine. By-products could be very important for the profitability of a mine and if they are not considered in the analysis there is a high risk of overestimate variable and marginal costs. It is transformed into copper equivalent units using 1992 copper prices.

Reserves: Ore reserves accounts for part of the mineral resource for which appropriate assessments have been carried out to demonstrate at a given date that extraction could be reasonably justified in terms of mining, economic, legal and environmental factors.

Ore Grade: Percentage of copper content in the ore body.

Realized Grade: Percentage of equivalent copper content in the ore body (including by-products).

Table 4.1: Copper Mines Panel Data 1992-2010. Summary Statistics

Variable (measurement units)	Units[1]	Obs.	Mean	Std. Dev.	Min	Max
Mine-Year level data						
Number of active mines	mines	19	172.8	26.4	144.0	226.0
Capacity	kt of cu	2672	86.36	146.89	0.25	1500.00
Copper production	kt of cu	3284	64.51	127.53	0.00	1443.54
By-products production[2]	kt of equivalent cu	3284	23.75	61.42	0.00	809.10
Ore mined	mt of ore	3261	11.48	25.68	0.006	314.21
Reserves	mt of ore	2687	253.16	533.14	0.02	5730.15
Copper ore grade	%	2630	1.21	1.22	0.02	11.42
Copper realized grade	%	3279	0.97	1.11	0.00	10.96
Copper equiv. realized grade	%	3279	2.25	2.03	0.01	15.17
Number of workers	workers	3270	1584.49	3499.01	18.00	48750.00
Labor cost	US $ / t cu equiv.	3270	445.68	559.55	38.90	21277
Electricity consumption	Kwh/t treated ore	3011	78.70	299.26	1.13	7530.96
Electricity unit cost	US Cents/Kwh	3276	5.27	2.88	0.26	35.00
Fuel consumption	litres/t treated ore	3253	1.60	1.36	0.00	21.52
Fuel unit cost	US Cents/Litre	3260	44.48	26.16	0.70	156.00
Market-Year level data						
LME Price	US$/t	19	3375	2097	1559	7550
World consumption	mt	19	13.04	2.17	9.46	16.33
World production	mt	19	13.10	2.24	9.50	16.17
World capacity	mt	19	14.78	2.87	10.82	19.81
Total production in our sample	mt	19	11.14	2.34	7.28	13.95
Total capacity in our sample	mt	19	12.84	2.49	9.11	16.92

Source: Codelco

Note (1): t represents metric tonnes (1,000 Kg), kt thousand of metric tonnes, and mt million of metric tonnes.

Note (2): By-product production is transformed into copper equivalent production using 1992 copper price.

4.2 Descriptive Evidence

In this section, we use our dataset to present descriptive evidence on four features in the operation of copper mines that have been often neglected in previous econometric models: (a) the high concentration of market shares in very few mines, and indirect evidence of market power and strategic behavior; (b) the lumpiness of investment; (c) the importance of production decisions at the extensive, i.e., active / inactive decision; and (d) the very large heterogeneity across mines in unit costs and geological characteristics.

4.2.1 Concentration of Market Shares

The international copper market structure, as many other mineral industries, is characterized by a reduced number of mines that account for a very large proportion of world production. Table 4.2 presents the market shares of the leading copper mines in 1996. Escondida (BHP-Billiton) and the Chilean state-owned mine, Chuquicamata (Codelco), have dominated the market with the 16% of world copper production. Some changes in the industry have undergone in the last decade as new mines are discovered. For example, Collahuasi (Xstrata) and Los Pelambres (Antofagasta Minerals), two world-class mines located in Chile have been developed since then and were ranked fourth and seventh, respectively, in 2010. However, in general, market shares and concentration ratios have remained relatively stable over the sample period.

Table 4.2: Market Shares and Concentration Ratios: Year 1996

Rank in 1996	Mine (Country)	Annual production (thousand Mt)	Share %	Con. Ratio CR(n) %
1.	**Escondida (Chile)**	825	9.1	9.1
2.	**Chuquicamata (Chile)**	623	6.9	16.0
3.	**Grasberg (Indonesia)**	507	5.5	21.5
4.	**Morenci (Arizona, USA)**	462	5.1	26.6
5.	**KGHM (Poland)**	409	4.4	31.0
6.	**El Teniente (Chile)**	344	3.8	34.8
7.	**ZCCM (Zambia)**	314	3.4	38.2
8.	**Bingham C. (Utah, USA)**	290	3.2	41.4
9.	**Ok Tedi (Papua)**	179	2.0	43.4
10.	**La Caridad (Mexico)**	176	2.0	45.4

4.2.2 Lumpy Investment in Capacity

Table 4.3 present the empirical distribution of investment rate in capacity, $i_{it} \equiv (k_{it} - k_{it-1})/k_{it-1}$, for the subsample of observations where the firm is active at two consecutive years. Investment is very lumpy, with a high proportion of observations with zero investment, and large investment rates when positive.

Table 4.3: Empirical Distribution Investment Rate in Capacity

Statistic	1993	1997	2001	2005	2009
% Obs. Zero Investment	80.0%	41.6%	45.0%	60.3%	69.8%
Conditional on positive					
Pctile 25%	12.5%	6.2%	6.2%	4.0%	7.8%
Pctile 50%	20.0%	16.2%	20.0%	21.7%	37.5%
Pctile 75%	100.0%	31.6%	100.0%	80.0%	116.6%

Source: Codelco

4.2.3 Active / Inactive Decision

Figure 4.1 presents the evolution of the number of active mines and the LME copper price during the period 1992-2010. The evolution of the number of active mines follows closely the evolution of copper price in the international market, though the series of price shows more volatility. The correlation between the two series is 0.89. However, market price and aggregate market conditions are not the only important factors affecting the evolution of the number of active mines. Mine idiosyncratic factors play an important role too. As shown in figure 4.2 and in table 4.4, this adjustment in the number of active mines is the result of very substantial amount of simultaneous entry (re-opening) and exit (temporary closing) decisions.

Figure 4.1: Evolution of the Number of Active Mines: 1992-2010

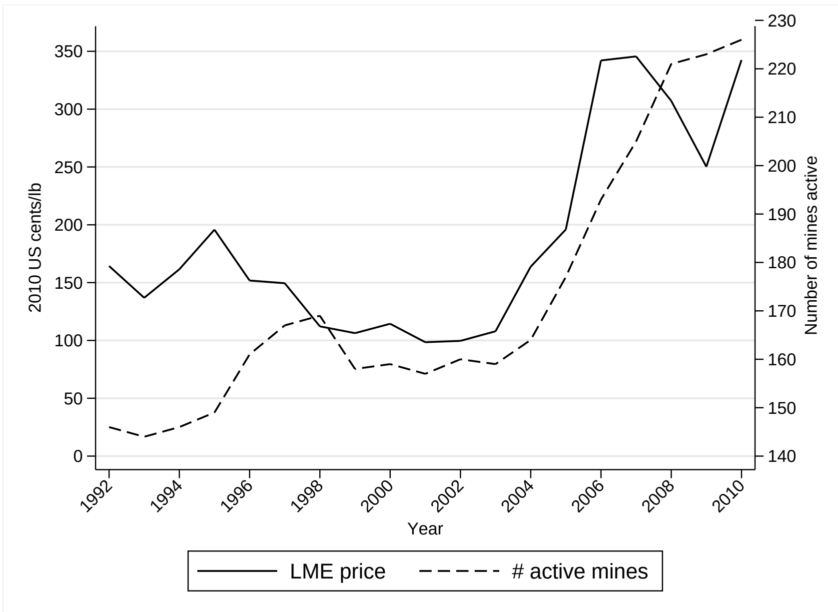


Figure 4.2: Entry (Re-opening) and Exit (Temporary Closings) Rates of Mines: 1992-2010

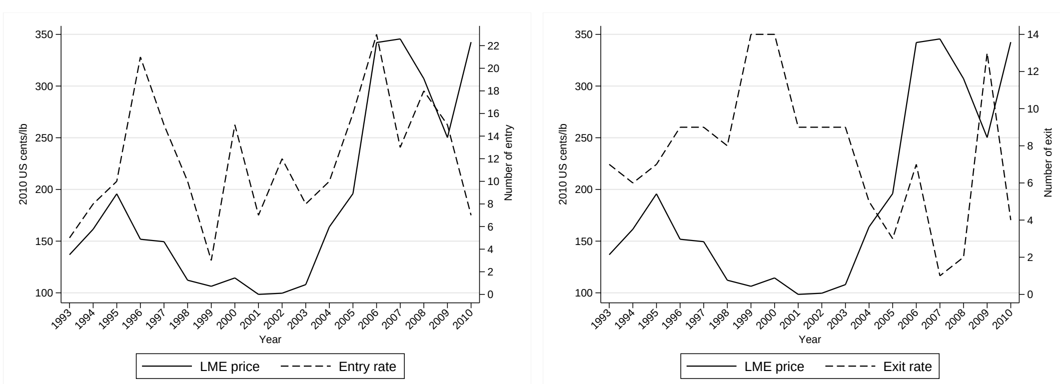


Table 4.4: Number of Mines, Entries and Exits

Variable	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**
# Active mines	146	144	146	149	161	167	169	158	159	157
Entries	-	5	8	10	21	15	10	3	15	7
Exits	-	7	6	7	9	9	8	14	14	9

Variable	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**
# Active mines	160	159	164	177	193	205	221	223	226	-
Entries	12	8	10	16	23	13	18	15	7	
Exits	9	9	5	3	7	1	2	13	4	-

Source: Codelco

Table 4.5 presents estimates of a probit model for the decision of exit (closing) that provide reduced form evidence on the effects of different market and mine characteristics on this decision. We present estimates both from standard (pooled) and fixed effect estimations, and report coefficients and marginal effects evaluated at sample means. The fixed effect Probit provides more sensible results: the signs of all the estimated effects are as expected, in particular, the effect of market price is positive and significant; and the marginal effects of the mine cost and ore grade variables become stronger. The smaller marginal effect of ore reserves in the FE Probit has also an economic interpretation: the mine fixed effect is capturing most of the "expected lifetime" effect (see the very substantial increase in the standard error), and the remaining effect captured by reserves is mainly through current costs. The estimates show that mine-specific state variables play a key role in the decision of staying active. The effect of ore grade is particularly important: doubling ore grade from the sample average 1.23% to 2.66% (percentile 85) implies an increase in the probability of staying active of almost 12 percentage points.

Figure 4.3 shows the estimated probability of an incumbent staying active varies with ore grade. Figure 4.4 presents this probability as a function of the mine average cost (C1). In this case, the higher the cost, the less likely an incumbent mine remain active.

Table 4.5: Reduced Form Probit for "Stay Active"(1)

Variable	Probit	Marginal effect	FE Probit	Marginal effect
ln(Price LME)[t]	-0.0681	-0.0201	0.520***	0.101***
	(0.0473)	(0.0139)	(0.140)	(0.0270)
ln(mine Avg. cost)[t-1]	-0.290***	-0.0857***	-1.940***	-0.377***
	(0.0442)	(0.0128)	(0.214)	(0.0401)
ln(Ore reserves)[t-1]	0.125***	0.0368***	0.235***	0.0456***
	(0.0108)	(0.00303)	(0.0697)	(0.0135)
ln(Ore grade)[t-1]	0.0242	0.00714	0.591***	0.115***
	(0.0276)	(0.00815)	(0.167)	(0.0322)
Number of obs.	3243		2233	
Log-likelihood	-1697.4		-784.9	

Note (1): Subsample of mines active at year t-1. Dependent variable: Dummy "Mine active at year t".

Note (2): * = significant at 10%; ** = significant at 5%; *** = significant at 1%;

4.2.4 Large Heterogeneity Across Mines

There is very large heterogeneity across mines in geological characteristics, such as reserves, metal ores and ore grade, but also in capacity, production and average costs. The degree of this heterogeneity is larger than what we typically find in manufacturing industries. Nature generates very different endowments of metals, ore grade and

Figure 4.3: Probability for Incumbent Staying Active by Ore Grade Level

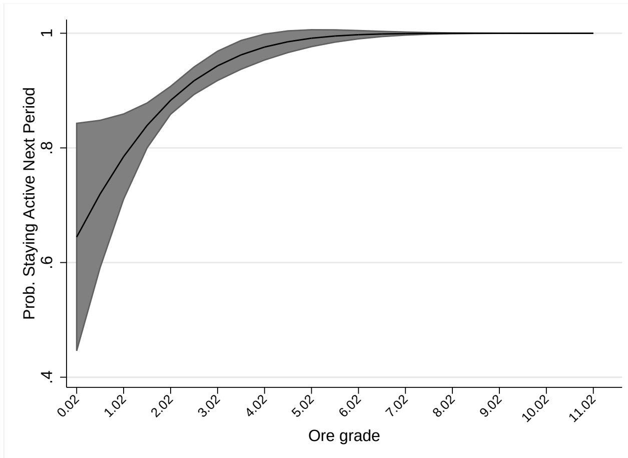
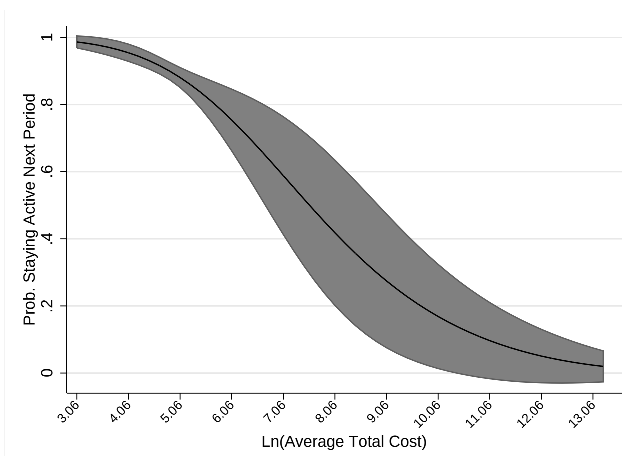


Figure 4.4: Probability for Incumbent Staying Active by Average Cost Level



reserves across mines, and investment decisions tend to be complementary with these endowments such that they amplify differences across mines.

Copper mines frequently produce a variety set of metals as by-products of copper. The metal mix of by-products could include cobalt, nickel, lead, zinc, molybdenum, gold and silver depending on geological and geographical characteristics. Therefore, there is a high degree of heterogeneity in the mix of metal production across mines. In our sample, a mine produces typically two by-products and the maximum is four. However, the mine's by-product mix remains relatively constant over time. Ignoring the importance of by-products in the final output results in misleading estimates of both variable and marginal costs. Therefore, in order to take into account the role of by-products in mine's output, we transform the production of each metal in copper equivalent units. Table 4.6 presents the mean share distributions of production for each metal across mines, it also presents the number of mines producing each metal and the number of mines for which is their main metal. Most of the mines produce silver and gold as by-products and 284 mines produce at least one by-product. Surprisingly, for 125 mines a single metal different than copper was their main product and for 129 mines the 50% or more of their production is coming from aggregate metals other than copper.

Table 4.6: Metal Share Mix Across Mines

Percentile[1]	Copper	Cobalt	Nickel	Lead	Zinc	Molybdenum	Gold	Silver
Pctile 1%	0.0038	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Pctile 5%	0.0234	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Pctile 10%	0.0465	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Pctile 25%	0.1612	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001
Pctile 50%	0.7600	0.0000	0.0000	0.0000	0.0000	0.0000	0.0047	0.0104
Pctile 75%	0.9655	0.0000	0.0000	0.0117	0.4904	0.0000	0.0660	0.0417
Pctile 90%	1.0000	0.0000	0.0000	0.0959	0.7650	0.0017	0.2174	0.1253
Pctile 95%	1.0000	0.0530	0.0000	0.1430	0.8383	0.0259	0.4332	0.2525
Pctile 99%	1.0000	0.5148	0.7322	0.3804	0.9315	0.1548	0.6641	0.3768
Mean	0.6016	0.0134	0.0197	0.0290	0.2211	0.0045	0.0678	0.0429
Std. Dev.	0.3820	0.0719	0.1190	0.0855	0.3155	0.0211	0.1412	0.0855
Min	0.0013	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Max	1.0000	0.6317	0.9079	0.8769	0.9676	0.1928	0.8007	0.6754
Obs	330	330	330	330	330	330	330	330

Mines With Positive Production of Metal

	Copper	Cobalt	Nickel	Lead	Zinc	Molybdenum	Gold	Silver
# Mines	330	18	9	93	130	36	191	248
Main metal	205	4	9	3	93	0	12	4

Source: Codelco

Note (1): Cross-sectional distribution of mean values for each mine.

We have measures of ore grade for each mine-year observation both for copper only (i.e., copper output per extracted ore volume) and for the copper equivalent output measure that takes into account by-products (i.e., copper equivalent output per extracted ore volume). Both measures present a similar heterogeneity across mines. Table 4.7 shows that the differences in realized ore grade imply that two mines with exactly the same amount of inputs but different ore grades produce very different amount of output: a mine in percentile 75 would produce double than a median mine (i.e., 3.42/1.71), and five times the amount of output of a mine in percentile 25.

Table 4.7: Heterogeneity Across Mines

Percentile[1]	Realized Grade (%)	Reserves (million t ore)	Production (thousand t)	Capacity (thousand t)	Avg. Total Cost ($/t cu)	Avg. Cost C1 ($/t cu)
Pctile 1%	0.14	0.11	0.01	0.05	908.80	450.94
Pctile 5%	0.26	0.60	0.04	0.42	1047.11	1021.50
Pctile 10%	0.39	1.11	0.16	0.95	1196.84	1287.78
Pctile 25%	0.75	3.66	1.09	2.79	1686.25	1632.94
Pctile 50%	1.71	13.48	5.10	8.58	2658.43	2067.43
Pctile 75%	3.42	120.61	22.72	38.00	8633.27	2638.71
Pctile 90%	5.16	541.99	96.50	151.37	33972.39	3867.84
Pctile 95%	6.28	978.48	156.23	203.79	80417.01	4968.07
Pctile 99%	8.99	2039.28	426.18	653.84	806386.06	7691.77

Source: Codelco

Note (1): Cross-sectional distribution of mean values for each mine.

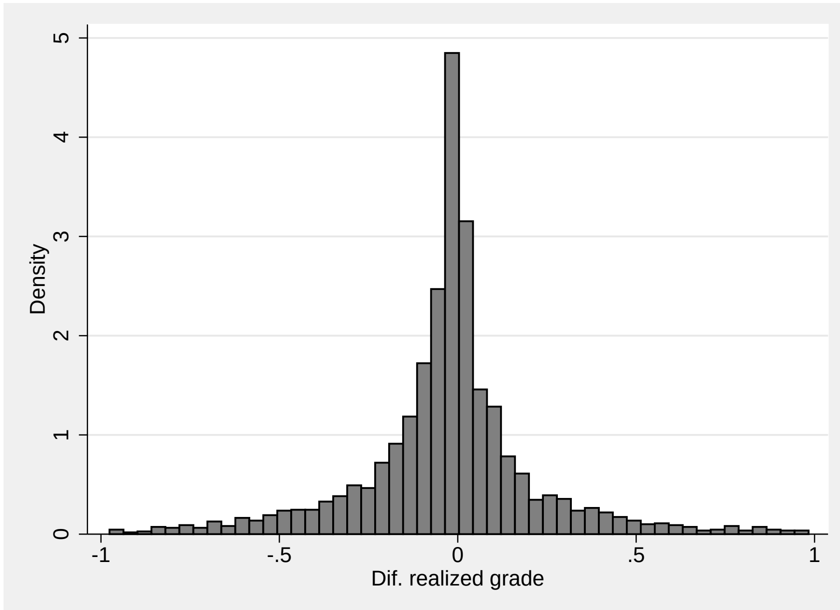
5

Endogenous Ore Grade and Evidence of Depletion Effect

There is substantial time variation of realized ore grade within a mine. Figure 5.1 presents the empirical distribution for the change in realized ore grade (truncated at percentiles 2% and 98%). The median and the mode of this distribution is zero (almost 30% of the observations are zero), but there are substantial deviations from this median value. To interpret the magnitude of these changes, it is useful to take into account that the mean realized grade is 2.25%, and therefore changes in realized grade with magnitude -0.25 and -0.02 represent, ceteris paribus, roughly 10% and 1% reductions in output and productivity. Since the 10th percentile is -0.25, we have that for one-tenth of the mine-year observations the decline in ore grade can generate reductions in productivity of more than 10%.

Figure 5.2 and table 5.1 present reduced form evidence on the evolution of realized grade over time. Time is number of years active (production > 0). Grades tend to

Figure 5.1: Empirical Distribution of Time Change in Ore Grade



decrease over active periods. This evidence is consistent with a depletion effect. Moreover, grade levels depreciate at different rates across mines according to size, which is mainly given by geological characteristics. For example, large mines present lower grades and lower grade depreciation rates whereas small and medium size mines have higher grades and higher grade depreciation rates. In general, there is no evidence to support that better mines (high initial grades) leave longer as this also depends on reserves and technology. This would indicate that small and medium size mines are exhausted faster which is consistent with the average years being active. However, older mines present a higher grade in the tail of the sample for all sizes.

Figure 5.2: Evolution of Ore Grade by Years of Production

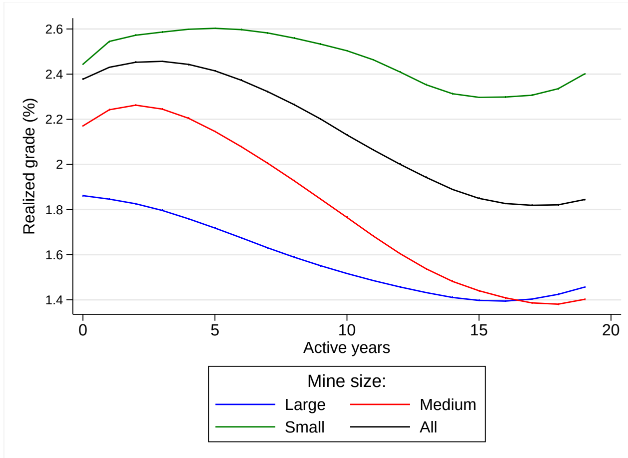


Table 5.1: Realized Ore Grade Descriptive Statistics

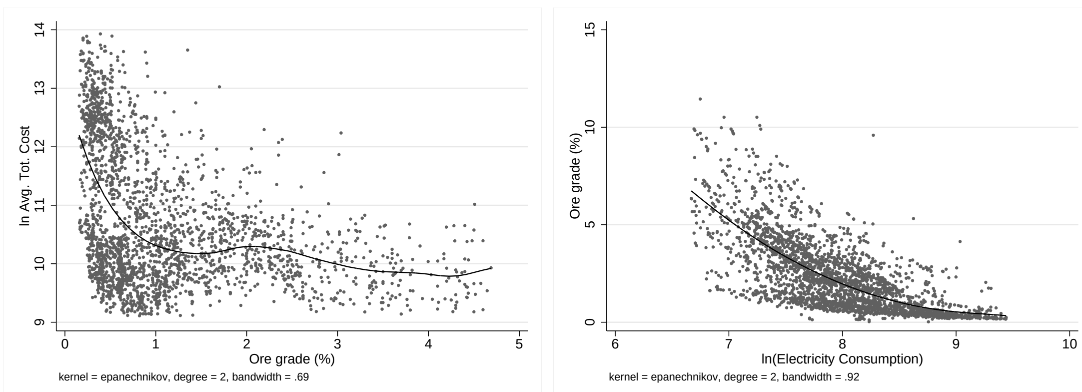
	Mine Size			All
	Large	Medium	Small	
# Mines	18	81	231	330
(%)	5.5	24.5	70	100
Realized grade (%)	1.6	1.89	2.52	2.25
Real. grade dep. rate (%)	-0.40	-1.42	-0.94	-1.29
Years active	14.83	12.91	8.53	9.95

Mean Realized Grade for all Mines

	Years Active			
Age of the Mine	1-5	6-10	11-15	15-19
1-5	2.38	-	-	-
6-10	2.99	2.54	-	-
11-15	2.29	2.34	1.91	-
15-19	2.20	2.10	1.96	1.82

Figure 5.3 presents reduced form evidence on the relationship between the total average production costs, demand for inputs and ore grade (truncated at percentiles 2% and 98%). Mines with lower grades presents higher production costs, f.i. the lower the ore grade the more processing of ore is needed to produce the same amount of copper and therefore the higher is the cost. Moreover, the aging of mines or the depletion effect, as described above, implies an increase in demand for inputs such as electricity, fuel and other inputs, as shown in the right graph of figure 5.3 for the case of electricity consumption.

Figure 5.3: Production Cost, Electricity Consumption and Ore Grade



5.1 Empirical Evidence of Depletion Effect

One of the most important questions that we study in this thesis is how much of these changes in grades are endogenous in the sense that they depend on the depletion or production rate of a mine. More specifically, current production decreases the quality or grade of the mine and this, in turn, increases future production costs. On the other hand, investments in exploration can improve not only the amount of reserves but also the grade levels. Table 5.2 presents estimates of our dynamic model that support this hypothesis. The empirical representation of equation (3.1.11) to estimate is:

$$\ln\left(\text{Grade}_{it}\right) - \ln\left(\text{Grade}_{it-1}\right) = \beta_1 \ \ln\left(1 + \text{Output}_{it-1}\right) + \beta_2 \ \text{Discovery}_{it} + \alpha_i + \gamma_t + u_{it} \tag{5.1.1}$$

where "Grade" is our realized measure of ore grade, "Output" is the mine production in copper equivalents units and "Discovery" is a binary indicator that is equal to 1 if the mine reserves increase by 20% or more, and it is zero otherwise. The estimates show a significant relationship between the change in the realized ore grade at period t and depletion (production) at $t-1$ after controlling for mine fixed effects and time effects. Doubling output is related to a reduction of almost 7% in realized ore grade. In others words, we have that increasing today's output by 100% implies a 7% reduction in the mine productivity next year. This is a non-negligible dynamic effect.

Table 5.2: Estimation for Dynamics of Realized Ore Grade(1)

	OLS			
Variable	ln(grade) [t]	ln(grade) [t]	Dif. ln(grade) [t]	Dif. ln(grade) [t]
ln(grade) [t-1]	0.9812***	0.9812***	1.000	1.000
	(0.007)	(0.007)	(-)	(-)
ln(output)[t-1]	-0.0181***	-0.0181***	-0.0159***	-0.0159***
	(0.005)	(0.005)	(0.004)	(0.004)
Discovery[t]		0.0004		-0.0028
		(0.008)		(0.008)
Number of obs.	2918	2918	2918	2918
m1 p-value	0.9180	0.9177	0.8020	0.8006
m2 p-value	0.3802	0.3811	0.1173	0.1137
	Fixed Effect			
Variable	ln(grade) [t]	ln(grade) [t]	Dif. ln(grade) [t]	Dif. ln(grade) [t]
ln(grade) [t-1]	0.6937***	0.6936***	1.000	1.000
	(0.040)	(0.040)	(-)	(-)
ln(output)[t-1]	-0.0458***	-0.0458***	-0.0973***	-0.0972***
	(0.013)	(0.013)	(0.015)	(0.015)
Discovery[t]		0.0064		0.0054
		(0.009)		(0.010)
Number of obs.	2918	2918	2918	2918
m1 p-value	0.2747	0.2769	0.0289	0.0288
m2 p-value	0.3417	0.3543	0.0003	0.0003
	Blundell and Bond			
Variable	ln(grade) [t]	ln(grade) [t]	Dif. ln(grade) [t]	Dif. ln(grade) [t]
ln(grade) [t-1]	0.9091***	0.9062***	1.000	1.000
	(0.051)	(0.052)	(-)	(-)
ln(output)[t-1]	-0.0710**	-0.0708**	-0.0686***	-0.0684***
	(0.029)	(0.029)	(0.026)	(0.026)
Discovery[t]		0.0126		0.0008
		(0.016)		(0.011)
Number of obs.	2918	2918	2918	2918
m1 p-value	0.0001	0.0001	0.0001	0.0001
m2 p-value	0.9952	0.9884	0.9631	0.9666
Hansen p-value	0.1969	0.1955	0.1547	0.1503
RW(3)	0.0754	0.0733		

Note (1): Subsample of mines active at years t-1 and t.

Note (2): * = significant at 10%; ** = significant at 5%; *** = significant at 1%.

Note (3): RW is Wald test for random walk in the lagged dependent variable.

Note (4): Year dummies included in all models.

5.2 Econometric Analysis of the Depletion Effect

In this section, we comment in more detail these estimates and the main econometric issues.

Equation (3.1.11) in the theoretical model presents the specification of the transition rule of ore grade. If the mine is inactive ($q_{it} = 0$), the evolution of the logarithm of ore grade is governed by a random walk $\ln(g_{i,t+1}) - \ln(g_{it}) = \delta_z^{(g)} z_{it}^{(r)} + \varepsilon_{it+1}^{(g)}$, where $\delta_z^{(g)} z_{it}^{(r)} + \varepsilon_{it+1}^{(g)}$ represent new discoveries and natural events affecting the mine. The term $-\delta_q^{(g)} \ln(1 + q_{it})$ captures the depletion effect on ore grade, where $\delta_q^{(g)} > 0$ is the depletion elasticity. Table 5.2 emphasizes the importance of dynamics and depletion in ore grade.

The main econometric concern in the estimation of equation (3.1.11) comes from the potential correlation between output q_{it} and the unobservable shock $\varepsilon_{it+1}^{(g)}$. For instance, suppose that new discoveries have positive serial correlation (i.e., $cov(\varepsilon_{it}^{(g)}, \varepsilon_{it+1}^{(g)}) > 0$) and that new discoveries at period t have a positive impact on output (as we would expect from our dynamic decision model). Under these conditions, OLS estimation of equation (3.1.11) provides an under-estimation of the depletion effect, i.e., the OLS estimate of $\delta_q^{(g)}$ is upward biased.[1] Our OLS estimates of the depletion elasticity, in the top panel of table 5.2, are between -0.016 and -0.018. However, we find strong positive serial correlation in the OLS residuals, what indicates that these estimates are inconsistent. To control for potential changes in grade due to new discoveries in reserves, we include a discovery dummy, $z_{it}^{(r)}$, for changes in the level of reserves of at least 20%. However, in none of our specifications new discoveries seems to play a role for changes in realized grades.

We deal with this endogeneity problem using standard methods in the econometrics of dynamic panel data models. We assume that the error has the following variance-

[1]Another potential source of bias in our estimates is because of measurement error. Since our measure of output contains a conversion of by-products to a copper equivalents units of output, any error in this measurement, which is uncorrelated with the fixed characteristic of the mine, would imply that the depletion effect is further underestimated.

components structure: $\varepsilon_{it+1}^{(g)} = \alpha_i^{(g)} + \gamma_{t+1}^{(g)} + u_{i,t+1}^{(g)}$, where the term $\alpha_i^{(g)}$ denotes time-invariant differences in realized grades across mines such as geological characteristics. $\gamma_{t+1}^{(g)}$ is an aggregate shock affecting all mines and $u_{i,t+1}^{(g)}$ is a mine idiosyncratic shock that is assumed not serially correlated over time. Under the assumption of no serial correlation in the transitory shock, we have that output at period t is not correlated with $u_{i,t+1}^{(g)}$. Since we have a relatively large number of mines in our sample, we can control for the aggregate shocks $\gamma_{t+1}^{(g)}$ using time dummies. In principle, if our sample included also a large number of years for each mine, we could also control for the individual effects $\alpha_i^{(g)}$ by using mine dummies. This is the approach in the Fixed Effects estimation presented in the second panel in Table 5.2. The fixed-effect estimates of the depletion elasticity are between -0.046 and -0.097 that are substantially larger than the OLS estimates. As we expected, controlling for persistent unobservables in innovation $\varepsilon_{it+1}^{(g)}$ contributes to reduce the OLS downward bias in depletion elasticity. However, as it is well known in the dynamic panel data literature, this fixed effects estimator can be seriously biased when the number of time periods in the sample is smaller than $T = 20$ or $T = 30$. The most common approach to deal with this problem is the GMM estimators proposed by Arellano and Bond (1991) and Blundell and Bond (1998). Since the parameter for the lagged ore grade is very close to one and the Arellano-Bond estimator suffers of a weak instruments problem in that situation, here we use the System GMM estimator proposed by Blundell and Bond. Our GMM estimates of the depletion elasticity, in the bottom panel in Table 5.2, are between -0.068 (s.e. = 0.026) and -0.071 (s.e. = 0.029). These estimates are very robust to imposing or not the restriction that lagged ore grade has a unit coefficient. As expected, the magnitude of the System GMM estimates of the effect of output in the evolution of realized grade is higher than those in the OLS estimates. The Arellano-Bond test of autocorrelation in the residuals cannot reject zero second-order autocorrelation in first differences. This evidence support the key assumption for identification of no serial correlation in the error term. The Hansen test for over-identifying restrictions does not reject the validity of the instruments. The estimated coefficient for lagged ore grade is close to 1 and, using a Wald test, we cannot reject the null hypothesis that it is equal to 1.

The main finding in our estimates of the transition function of the realized grade is that current output has a substantial negative effect on future ore grades. This dynamic depletion effect is not negligible. Our favorite specification states that increasing current output by 100% leads to a depreciation of 7% in the mine realized grades next period. Note that this is a long-run effect.

6

Production Function

In recent years, there has been renewed interest in the estimation of production functions mainly triggered by a significant methodological improvement in econometric tools and by the increasing availability of firm-level data. The estimation of production functions is an important component in many economic models. For example, it plays an important role to evaluate the efficiency of an industry, f.i. economies of scale and economies of scope, and to analyse the total factor productivity growth driven by changes in strategies or policies such as investment in R & D, tariff regulation or the adoption of a new technology.

The estimation of production functions, however, is subject to several econometric issues. The most important econometric problems in the identification of production functions are the simultaneity between output and variable inputs and the selection biases.

Intuitively, simultaneity arises because firms' unobserved productivity, for the econometrician but not for the firm, may be correlated with their input choices (Aguirregabiria, 2009; Olley and Pakes, 1996; Ackerberg et al., 2007). Specifically, firms will increase their use of variable inputs such as labor and materials as a result of a positive productivity shock. The correlation between variable inputs and productivity will introduce an upward bias in the OLS coefficient estimates of the variable inputs. Similarly, Levinsohn and Petrin (2003) show that OLS estimation of the production function will lead to a downward estimation of capital.

The selection bias emerges because firms with a low productivity level will be more likely to exit the market, and in turn the dataset, than firms with a high productivity level. In addition, the probability that a firm exit from the market is correlated with the firm size or capital stock. Therefore, firms with a large capital stock will be more likely to stay in the market, even with a low productivity level, than those firms with a small capital supply. This negative correlation between the size of the firm and the probability of exit for a given productivity level would generate downward estimates of the capital coefficient (Yasar et al., 2008).

Other common issues in the estimation of production functions include measurement error and specification problems. Given that, typically, quantities are not observable for the researcher, deflated sales and aggregated prices are used as proxy for output and inputs. However, if firm-level prices variation is negatively correlated with output, which in turn is positively correlated with input choices, the coefficient of variable inputs will be estimated with downward bias (Van Beveren, 2012). Specification problems that would lead to a bias in the estimation of the coefficients in the production function emerge when firms produce multiple products and these products are produced with different technologies or when firms use different types of inputs that can be complementary or substitutes and the econometrician does not take into account this level of detail in her specification.

Different approaches have been proposed to deal with these issues. We will briefly describe the intuition of some common solutions to the simultaneity and selection problems. The traditional methods to solve the endogeneity problem have been instrumental variables and fixed effects (Ackerberg et al., 2007). First, given that the unobserved productivity shock and the choice of inputs are simultaneously determined, the idea behind instrumental variables is to use input prices as instruments for labor (or variable inputs) and capital. Input prices are correlated with input choices but not with the productivity shock as long as input markets are competitive. However, as Ackerberg et al. (2007) state, there are some issues when using instrumental variables. Price of inputs are not always available for the researchers, and when available they may not have significant variation across firms, f.i. input prices typically are measured at national markets. Moreover, if we observe input prices and they have enough sample variation, they can reflect differences in unobserved input quality rather than differences in exogenous input market conditions. For example, differences in the quality of labor could be correlated with differences in productivity as high wages will attract high quality workers that will increase the productivity. Therefore, wages are correlated with productivity and wages are not longer good instruments.

A second approach to deal with simultaneity issues is the estimation of fixed effects. Taking advantage of panel datasets, fixed effects estimation assumes that the unobserved productivity shock is constant over time. Therefore, we could obtain consistent estimates of the production function parameters by using mean or first differences (Ackerberg et al., 2007). However, assuming that the productivity shock is time-invariant is very unrealistic. Typically, we are interested in to analyse the dynamics of the productivity, so if the productivity shock is not time-invariant, then fixed effects will not solve the endogeneity problem and mean and first differences will be biased. In other words, fixed effects assumes that the productivity shock is realized after the firm decides the amount of inputs to use (Aguirregabiria, 2009). Fixed effects, in practice, will lead to a downward bias in the estimation of the capital coefficient.

More recent solutions to the simultaneity problem are dynamic panel models and control function approaches. The Dynamic Panel Method, proposed by Arellano and Bond (1991), relax the assumption of the strictly exogeneity of inputs and estimate the parameters in the production function by first-differencing the production function and using as instruments lagged inputs rather than input prices to solve for the endogeneity problem. A key assumption for identification in this method is that the productivity shock is not serially correlated (Aguirregabiria, 2009). However, a well known problem of this estimator is the weak instruments problem, if inputs are persistent over time, then lagged levels of inputs will be weakly correlated with differences in inputs. A consequence of this is that coefficients of labor and capital will be downward biased. Blundell and Bond (2000) propose a system-GMM estimator to solve the weak-instrument problem. The idea consists in to use lagged first-differences of the inputs as instruments for the equation in levels. Another advantages of this method are that it exploits the cross-sectional variation of input and output in the sample as it does not drop the fixed effect in the production function and it can be easily extended for autocorrelation of order one in the productivity shock (Aguirregabiria, 2009).

A popular solution in Industrial Organization for both endogeneity and simultaneity problems in the estimation of production functions has been proposed by Olley and Pakes (1996). The simultaneity problem is solved by using the firm's investment decisions to proxy for unobserved and time-varying productivity shocks whereas the selection issue is solved by controlling for endogenous exit (Van Beveren, 2012; Yasar et al., 2008; Aguirregabiria, 2009). Olley and Pakes approach requires several assumptions on the unobserved productivity and the timing of input choices. First, the productivity shock follows a first-order Markov process. This is more general than the AR(1) assumption in the Dynamic Panel approach, however, it removes the cross sectional variation in the productivity shock (Ackerberg et al., 2007). Second, Olley and Pakes assume a timing of input choices and a dynamic nature of inputs. Timing refers to the time when input choices are made and dynamic of inputs implies that current choices of inputs impact future profits. For instance, in the OP approach labor is considered as a flexible and non-dynamic input because it is chosen at the current period and because current choices do not impact future costs. On the contrary, capital is assumed as a fixed and dynamic input because it is chosen at previous periods (time-to-build assumption) and because current choices of capital will have an effect on future profits. The final assumption in OP is the Strict Monotonicity assumption of the investment demand function. Firm's investment decision is a strictly increasing function in the productivity shocks (Ackerberg et al., 2007). This assumption implies that the firm's investment function is invertible, which allow us to recover the unobservable productivity shocks.

The OP procedure for the estimation of production functions consists in two-stages. In the first stage, variable inputs can be consistently estimated by OLS and using a control function for the productivity shock. Typically, this control function is approximated by a third or fourth order polynomial of the state variables, f.i. capital and investment. In the second stage, we use the Markov and timing assumptions to estimate the fixed and dynamic inputs, f.i., capital. We could run a Non-linear Least Square estimator or to apply a GMM estimator in the second stage depending on the timing assumptions of variable inputs. For a technical review of the OP procedure, the interested reader is referred to Ackerberg et al. (2007) and Aguirregabiria (2009). Several works have relaxed some of these assumptions and extended the OP method. For example, Levinsohn and Petrin (2003) have pointed out that a significant number of firms reports zero investments, which could imply ignoring an important part of the sample. In order to address this issue, LP proposed to use materials as proxy for unobserved productivity rather than investment. Ackerberg et al. (2006) have shown that if there exists cost of adjustment in labor, then labor will be a state variable and it will no longer be identified in the first stage. Therefore, ACF propose a method where only the unobserved productivity is recovered in the first step and the labor coefficient is identified in the second step.

It is not clear when a method is better than another. Some advocates of the OP approach argues that the Dynamic Panel approach lacks of economic justification for its assumptions. On the other hand, some assumptions in the OP approach can be considered as too strong. For example, Dynamic Panel approach does not requires the monotonicity assumption and allows for fixed effects in the productivity shocks. If fixed effects are part of the productivity shocks, then the OP approach would fail.

6.1 Production Function Estimates

This section presents estimates of the parameters of the production function proposed in chapter 3.

We estimate a Cobb-Douglas production function in terms of physical units for output, capital, labor, reserves, ore grade, and intermediate inputs electricity and fuel. The log-linearized production function is:

$$\ln q_{it} = \alpha_k \ \ln k_{it} + \alpha_\ell \ \ln \ell_{it} + \alpha_e \ \ln e_{it} + \alpha_f \ \ln f_{it} + \alpha_g \ \ln g_{it} + \alpha_r \ \ln r_{it} + \omega_{it} + e_{it} \tag{6.1.1}$$

where the input variables are capital, k, labor, ℓ, electricity, e, fuel, f, ore grade, g, and reserves, r. ω_{it} is a productivity shock and e_{it} represents a measurement error in output or any shock that is unknown to the mine when it decides the quantity of inputs to use. The estimation of the parameters in this function should deal with the aforementioned endogeneity problem due to the simultaneous determination of inputs and output. Here, we present estimates from two different methods, as mentioned above, that deal with this problem: dynamic panel data methods proposed by Arellano and Bond (1991) and Blundell and Bond (1998); and control function approach methods proposed Olley and Pakes (1996) and Levinsohn and Petrin (2003).

Table 6.1 presents our estimations of production function parameters. We report estimates from six different specifications and methods. All the specifications include time dummies. Column (1) reports fixed effect estimates (OLS with mine dummies) based on the assumption that the productivity shock follows a variance-components structure $\omega_{it} = \eta_i + \gamma_t + \omega_{it}^*$, where η_i is a time-invariant mine specific effect such as some geological characteristics, and ω_{it}^* is not serially correlated and it is realized after the miner decides the amount of inputs to use at period t. Of course, the conditions for consistency of the fixed effects estimator are very strong.

Column (2) provides estimates using Arellano-Bond GMM method, based on the same covariance-structure for productivity, $\omega_{it} = \eta_i + \gamma_t + \omega_{it}^*$, and the assumption that ω_{it}^* is not serially correlated, but allowing for correlation between inputs and the productivity shock ω_{it}^{*}. In the equation in first differences at period t, $\Delta \ln q_{it} = \Delta \ln \mathbf{x}_{it}$ $\alpha + \Delta\omega_{it}^{*}$, inputs and output variables dated at $t-2$ and before are valid instruments for endogenous inputs: i.e., $\mathbb{E}(\ln \mathbf{x}_{it-2}\ \Delta\omega_{it}^{*}) = 0$ and $\mathbb{E}(\ln q_{it-2}\ \Delta\omega_{it}^{*}) = 0$. The assumption of no serial correlation in ω_{it}^{*} is key for the consistency of this estimator, but this assumption is testable: i.e., it implies no serial correlation of second order in the residuals in first differences, $\mathbb{E}(\Delta\omega_{it}^{*}\ \Delta\omega_{it-2}^{*}) = 0$.

Column (3) presents also estimates using Arellano-Bond GMM estimator but of a model where the productivity shock ω_{it}^{*} follows an AR(1) process, $\omega_{it}^{*} = \rho\, \omega_{it-1}^{*} + \xi_{it}$, where ξ_{it} is not serially correlated. In this model, we can apply a quasi-time-difference transformation, $(1-\rho\mathbb{L})$, that accounts for the AR(1) process in ω_{it}^{*}, and then a standard first difference transformation that eliminates the time-invariant individual effects. This transformation provides the equation, $\Delta \ln q_{it} = \rho\, \Delta \ln q_{it-1} + \Delta \ln \mathbf{x}_{it}\ \alpha + \Delta \ln \mathbf{x}_{it-1}$ $(-\rho\alpha) + \Delta\xi_{it}$, where inputs and output variables dated at $t-2$ and before are valid instruments: i.e., $\mathbb{E}(\ln \mathbf{x}_{it-2}\ \Delta\xi_{it}) = 0$ and $\mathbb{E}(\ln q_{it-2}\ \Delta\xi_{it}) = 0$.

Column (4) reports estimates using Blundell-Bond System GMM. As we have mentioned above for the estimation of the transition rule of ore grade, in the presence of persistent explanatory variables, the First-Difference GMM may suffer a weak instruments problem that implies substantial variance and finite sample bias of the estimator. In this case, the Blundell-Bond System GMM is preferred to Arellano-Bond method. This system GMM is based on two sets of moment conditions: the Arellano-Bond moment conditions, i.e., input variables in levels at $t-2$ and before are valid instruments in the equation in first differences at period t; and the Blundell-Bond moment conditions, i.e., input variables in first-differences at $t-1$ and before are valid instruments in the equation in levels at period t, $\mathbb{E}(\Delta \ln \mathbf{x}_{it-1}\ [\eta_i + \omega_{it}^{*}]) = 0$ and $\mathbb{E}(\Delta \ln q_{it-1}\ \omega_{it}^{*}) = 0$. As in the Arellano-Bond estimator, the assumption of no serial correlation in ω_{it}^{*} is fundamental for the validity of these moment conditions and the consistency of the estimator. Column (5) provides estimates using Blundell-Bond System GMM for the model where ω_{it}^{*} follows an AR(1) process.

Column (6) presents estimates using the control function approach of Olley and Pakes (1996) based in the extension proposed by Levinsohn and Petrin (2003). We use materials rather than investment as proxy for the productivity shock given the high degree of lumpiness in our investment measure. We also allow for adjustment costs in labor and introduce formally lagged labor as an state variable in the control function. A mine demand for materials, m_{it}, is given by $m_{it} = m_t(k_{it}, \ell_{it-1,} g_{it}, r_{it}, \omega_{it})$. Since this demand is strictly monotonic in the productivity shock, ω_{it}, there is an inverse function $\omega_{it} = m_t^{-1}(m_{it}, k_{it}, \ell_{it-1,} g_{it}, r_{it})$ and we can control for the unobserved productivity in the estimation of the production function by including a nonparametric function (i.e., high order polynomial) of the observables $(m_{it}, k_{it}, \ell_{it-1,} g_{it}, r_{it})$, such that, $\ln q_{it} = \alpha_\ell \ln \ell_{it} + \alpha_e \ln e_{it} + \alpha_f \ln f_{it} + \phi_t(m_{it}, k_{it}, \ell_{it-1,} g_{it}, r_{it}) + e_{it}$. In the first step of this method, parameters α_ℓ, α_e, and α_f, and the parameters in the polynomials ϕ_t are estimated by least squares. We use a third order polynomial function to approximate our control function. The parameters α_k, α_g, and α_r are estimated in a second step by exploiting the assumption that the productivity shock evolves following a first-order Markov process. For instance, if we assume that ω_{it} follows an AR(1) process,[1] $\omega_{it} = \rho\, \omega_{it-1} + \xi_{it}$, then the model implies the equation $\phi_{it} = \rho\, \phi_{it-1} + \alpha_k \ln k_{it} + (-\rho\alpha_k) \ln k_{it-1} + \alpha_g \ln g_{it} + (-\rho\alpha_g) \ln g_{it-1} + \alpha_r \ln r_{it} + (-\rho\alpha_r) \ln r_{it-1} + \xi_{it}$. All the regressors in this equation are pre-determined before period t and therefore not correlated with ξ_{it}. Given that ϕ_{it} has been estimated in the first step, this equation can be estimated by nonlinear least squares to obtain consistent estimates of α_k, α_g, α_r, and ρ.[2]

[1] Note that this assumption is different to the specification of the productivity shock in dynamic panel models. In the Olley-Pakes model, the whole productivity shock, ω_{it}, follows a Markov process. In dynamic panel data models, we have that $\omega_{it} = \eta_i + \omega^*_{it}$, and ω^*_{it} follows an AR(1) process.

[2] We experiment with many alternative specifications, however, results does not vary too much. We also allow for selection bias in the LP method but results are very similar.

Table 6.1: Production Function Estimates

	(1) FE no AR(1)	(2) FD-GMM no AR(1)	(3) FD-GMM AR(1)	(4) SYS-GMM no AR(1)	(5) SYS-GMM AR(1)	(6) LP
Capital	0.2417***	0.3728***	0.2431***	0.1265***	0.2206***	0.3328***
	(0.054)	(0.064)	(0.065)	(0.035)	(0.060)	(0.020)
Labor	0.1418***	0.1841*	0.0860	0.0319	0.0936*	0.0355
	(0.038)	(0.096)	(0.096)	(0.065)	(0.051)	(0.046)
Electricity	0.2229***	0.1335*	0.1835**	0.3217***	0.2316***	0.2063***
	(0.078)	(0.069)	(0.079)	(0.078)	(0.084)	(0.047)
Fuel	0.4001***	0.4755***	0.4547***	0.3582***	0.4372***	0.1609***
	(0.048)	(0.055)	(0.073)	(0.055)	(0.067)	(0.022)
Grade	0.7432***	0.6120***	0.7688***	0.6657***	0.6999***	0.5860***
	(0.069)	(0.142)	(0.122)	(0.055)	(0.068)	(0.032)
Reserves	0.0011	-0.0621**	-0.0211	0.0693***	0.0159	0.0062
	(0.014)	(0.030)	(0.026)	(0.017)	(0.015)	(0.012)
Output(t-1) (ρ)	-	-	0.5467***	-	0.5660***	-
	-	-	(0.074)	-	(0.060)	-
Obs.	2150	1906	1684	2150	1906	1719
m1-pvalue	0.0000	0.0296	0.0000	0.0459	0.0000	
m2-pvalue	0.0000	0.0112	0.4438	0.0264	0.4514	
Hansen -pvalue		0.9105	0.7569	1.0000	1.0000	
RTS	1.0076	1.1037	0.9464	0.9076	0.9989	0.7355
Null CRS	0.8449	0.2076	0.5706	0.0320	0.9825	

In Table 6.1, several important empirical results are robust across the different specifications and estimation methods. First, the production technology is very intensive in energy, both electricity and fuel. The sum of the parameters for energy and fuel, $\alpha_e + \alpha_f$, is always between 0.61 and 0.68 and represents approximately two thirds of the returns to scale of all the inputs. The technology is also relatively intense in capital, with a capital coefficient between 0.13 and 0.37. In contrast, the technology presents a low coefficient for labor, between 0.03 and 0.18. Second, the coefficient of ore grade is large and very significant, between 0.61 and 0.77. Ceteris paribus, we would expect a grade elasticity equal to one, i.e., keeping all the inputs constant, an increase in the ore grade should imply a proportional increase in output. The estimated elasticity, though high, is significantly lower than one. This could be explained by heterogeneity across mines. Mines with different ore grades may be also different in the type of mineral, hardness of the rock, depth of the mineral, or distance to the processing plant. Third, the estimated coefficient for reserves is always very small and not economically significant. Fourth, tests of serial correlation in the residuals in columns (2) and (4) reject the null hypothesis of no serial correlation of second order, and therefore reject the hypothesis that the shock ω_{it}^* is not serially correlated. The same test for the models in columns (3) and (5) (with an AR(1) process for ω_{it}^*) cannot reject the null hypothesis that the shock ξ_{it} in the AR(1) process is not serially correlated. Therefore, these tests clearly favor the specification with an AR(1) process for ω_{it}^*.

Based on the specification tests and on the economic interpretation of the results, our preferred specification and estimates are the ones in column (5). These estimates imply an industry very intensive in energy ($\alpha_e + \alpha_f = 0.67$) and capital ($\alpha_k = 0.23$) but not in labor ($\alpha_\ell = 0.09$), with constant returns to scale (i.e., $\mu = 0.99$, the hypothesis of CRS cannot be rejected), a sizeable effect of ore grade ($\alpha_g = 0.70$), and very persistent idiosyncratic productivity shocks.

6.2 Marginal Costs and Variable Costs

Given the estimated parameters of the production function, and the information on variable input prices, we calculate variable costs and marginal costs using the formula in equation (3.1.9). Table 6.2 presents the empirical distributions of variable cost, average variable cost, marginal cost, and the exogenous part (or predetermined part) of the marginal cost ($ExMC$) defined as the marginal cost of producing the first unit of output (i.e., the first ton of copper). We can interpret this exogenous marginal cost as the intercept of the marginal cost curve with the vertical axis at $q = 1$.

Table 6.2: Distribution of Estimated Marginal and Variable Costs[(1)]

Pctile.	**Marginal Cost**	**Ex. Marginal Cost**	**Variable Cost**	**AVC**
Pctile 1%	99.09	17.59	937.58	75.55
Pctile 5%	156.17	40.90	1,741.60	119.07
Pctile 10%	197.11	57.25	3,076.57	150.29
Pctile 25%	306.30	89.88	7,209.35	233.54
Pctile 50%	541.56	154.21	20,506.95	412.90
Pctile 75%	1,008.46	285.06	80,177.51	768.89
Pctile 90%	1,932.51	561.43	181,830.00	1,473.42
Pctile 95%	2,632.80	832.48	335,716.40	2,007.34
Pctile 99%	4,901.29	1,619.28	1,026,301.00	3,736.93
Mean	878.70	262.37	83,047.93	669.95
Std. Dev.	1104.82	354.02	189,853.30	842.36
Min	26.47	7.81	140.53	20.18
Max	15298.46	5,591.10	2,657,656.00	11,664.12
Obs	2102	2102	2102	2102

Note (1): values in US$ per ton.

There is very substantial heterogeneity across mines in all measures of variable cost. For the exogenous marginal cost, the interquartile difference is 217% (i.e., $(285.06 - 89.88)/89.88$), and the difference between the 90th and 10th percentiles is 880% (i.e., $(561.43 - 57.25)/57.25$). Interestingly, the degree of heterogeneity in marginal cost is similar to the heterogeneity in its exogenous component. This clearly contradicts the hypothesis of static perfect competition.

Table 6.3 provides a decomposition of the variance of the logarithm of the exogenous marginal cost into the contribution of its different components. The top-panel reports the variance-covariance matrix of the seven components of the (exogenous) marginal cost. The bottom panel presents the variance decomposition. By definition, the logarithm of the exogenous marginal cost (i.e., $\ln[ExMC]$) is equal to $\beta_\ell \ln(p_{it}^\ell)+$ $\beta_e \ln(p_{it}^e)+$ $\beta_f \ln(p_{it}^f)+$ $\beta_g \ln(g_{it})+$ $\beta_r \ln(r_{it})+$ $\beta_k \ln(k_{it})+$ $\beta_\omega \omega_{it}$, where $\beta_\ell = \alpha_\ell/(\alpha_\ell + \alpha_e + \alpha_f)$, $\beta_g = -\alpha_g/(\alpha_\ell + \alpha_e + \alpha_f)$, and so on. For each of its additive components, we calculate its covariance with $\ln[ExMC]$. This decomposition provides a measure of the contribution of each component to the heterogeneity in marginal costs. There are several interesting results. First, ore grade is, by far, the factor with the most important contribution to the heterogeneity in marginal costs across mines. If we eliminate that source of heterogeneity, keeping the rest of the elements constant, the variance of marginal costs would decline by 58%. Second, total factor productivity with 19% and fuel prices with 17% are the other most important sources of heterogeneous marginal costs. These three variables together account for 95% of the variance. Electricity prices have also a non-negligible contribution of 5.6%. Third, the contribution of capital to the dispersion of marginal costs is basically null. This is despite, our estimation of the production function, implies that capital has an important contribution to output and marginal cost, and also despite the variance of capital across mines is quite important (see top panel in this table). The explanation for this result comes from the correlation between capital and ore grade. Capital and ore grade have a strong negative correlation (i.e., correlation coefficient -0.47). Mines with poorer ore grades require typically more equipment both in extraction and in the processing stages. The contribution of capital to the variance of marginal costs is mostly offset by the fact that larger mines in terms of capital are typically associated with lower ore grades. Fourth, interestingly, the contribution of wages is zero.

Table 6.3: Variance Decomposition of Marginal Cost

Variance - Covariance Matrix$^{(1),(2)}$

(all variables in logarithms)

	Wage	Elect. p.	Fuel p.	Ore grade	Reserves	Capital	Product.
Wage	1.0526						
Electricity price	0.0469	0.2289					
Fuel price	0.0658	0.1069	0.3983				
Ore grade	0.0215	0.0127	0.0538	0.9265			
Reserves	0.1497	0.0015	-0.1834	-1.4527	5.5826		
Capital	0.3470	0.0139	-0.0864	-0.7434	2.9898	2.7069	
Productivity	0.0598	-0.0254	-0.0037	-0.0276	0.0162	-0.1177	0.1377

Variance Decomposition: Exogenous Part of Marginal Cost$^{(1),(2),(3)}$

x	Variance	Covariance	Weight (%)	Obs.
Marginal cost (Ex)	0.8384	0.8384	100.0	2102
Wage	0.0159	-0.0025	-0.30	2102
Electricity price	0.0211	0.0469	5.6	2102
Fuel price	0.1310	0.1452	17.3	2102
Ore grade	0.7806	0.4879	58.2	2102
Reserves	0.0024	-0.0051	-0.6	2102
Capital	0.2266	0.0033	0.4	2102
Productivity	0.2368	0.1627	19.4	2102

Note (1): All variables in logs.

Note (2): Weight is computed as $cov(\beta_x \ln[x], \ln[ExMC])/Var(\ln[ExMC])$.

Note (3): The number of observations is restricted to observed productivity from the estimation of the production function.

Figure 6.1 presents the evolution over time of the contribution of each component in the variance of the exogenous marginal costs. Weights remain relatively stable over the period. However, the contribution of the variance of productivity is decreasing over time. This decreasing effect of productivity could be capturing the extensive and intensive changes effects during the boom, as described below.

Figure 6.1: Evolution of Exogenous MC Components Weights

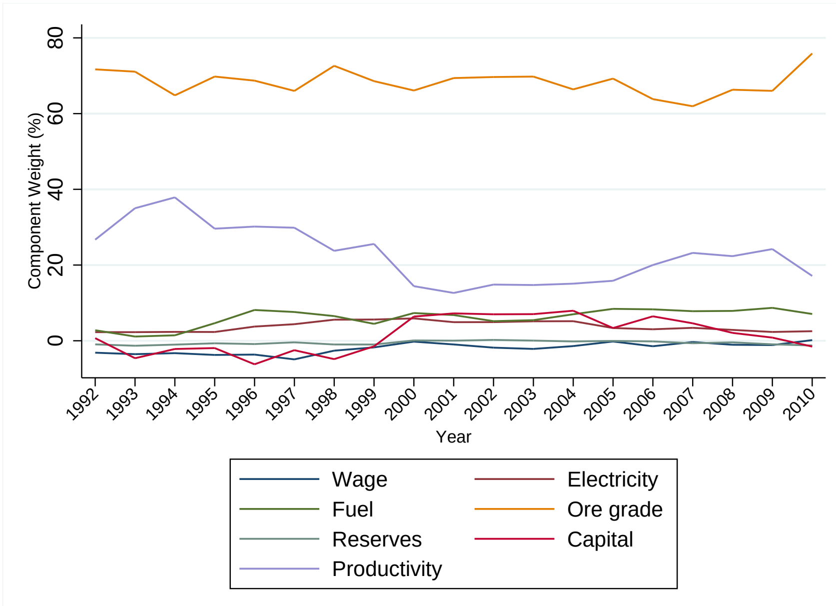


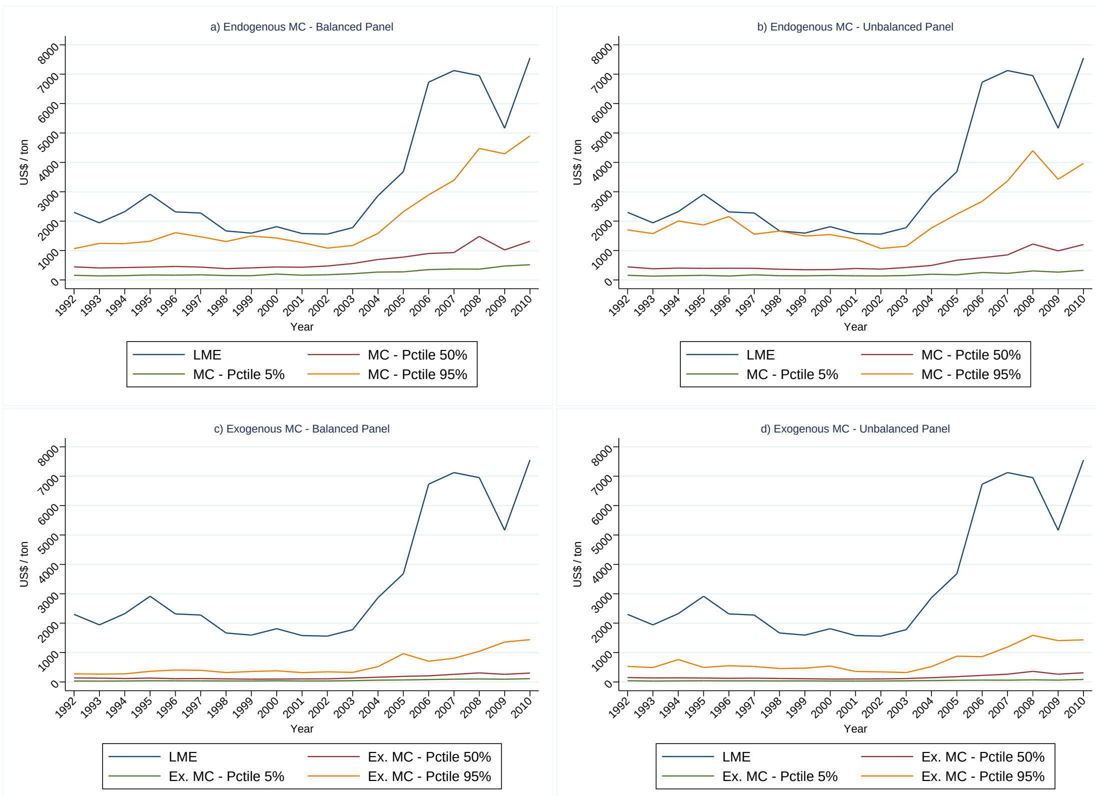
Figure 6.2 provides evidence on the relationship between the evolution of the LME copper price and the evolution of the 5th, 50th and 95th percentiles of the estimated marginal costs. We present figures both for the exogenous and for the total marginal cost, and for a balanced panel of 43 mines and an unbalanced panel of 212 mines. These figures provide an interesting description of the relationship between copper prices, marginal costs, and demand. First, panel (c) presents the evolution of $ExMC$ for the balanced panel of mines. This figure represents changes in marginal costs that are not associated to changes in the composition of active firms and are not related to the amount of output produced, i.e., to demand. We can see that there is a relatively modest increase in the marginal cost at the 95th percentile between 2003 and 2010. This modest increase can account only for a small portion of the observed increased in copper price during

this period. Panel (d) presents the evolution of $ExMC$ for the unbalanced panel. The evidence provided by this figure is similar as the one from panel (c): even if we take into account changes in the composition of mines, and more specifically the entry of less efficient mines due to increasing prices, the increase in the exogenous marginal cost accounts at most for one-fourth of the increase in price. Second, the comparison of panels (c) and (d) provides evidence that positive demand shocks promote entry of less efficient mines. For instance, the exogenous marginal costs of the mines at the 95th percentile in the unbalanced panel is a 16% higher than the exogenous marginal costs of those mines in the balanced panel. Third, panels (a) and (b) present the evolution of total (endogenous) marginal cost. Interestingly, the $95th$ percentile follows very closely the evolution of copper price, though the 5th and 50th percentiles are still quite flat. This picture seems consistent with the story that most of the price increase comes from the combination of a positive demand shock, but also with the fact that mines with relatively higher marginal costs have increased their production share during this period. Fourth, these figures show that some mines in this industry enjoy large markups in terms of marginal costs. Price is mainly determined by the marginal cost of less efficient mines, and given the high heterogeneity in marginal costs, most efficient mines have large markups.

6.3 Productivity Implications

Finally, we use the estimates from our favorite specification of the production function to analyze the evolution of the productivity growth. We follow Olley and Pakes (1996) and define the aggregated productivity of the industry as a weighted average productivity: $\Omega_t = \sum_{i=1}^{N_t} s_{it}\omega_{it}$, where s_{it} is the output share of mine i at period t. It is difficult to identify the drivers of the aggregated productivity growth. A recurrent claim made in the industry is that ore grades are an important determinant of productivity. Since we have controlled for ore grade in the estimation of the productivity, it is not possible to attribute a role of the depletion effect on the evolution of our measure of aggregated productivity . However, following the Olley and Pakes decomposition method, it is pos-

Figure 6.2: Evolution of Est. Marginal Cost and Exogenous Marginal Cost



sible to distinguish between two drivers of this productivity growth: reallocation and average productivity growth. The method consists in to decompose the aggregate productivity into a within component and the covariance between productivity and market share:

$$\Omega_t = \bar{\omega}_t + \sum_{i=1}^{N_t} (\Delta s_{it} \Delta \omega_{it}) = \bar{\omega}_t + \Psi_t^{s\omega} \tag{6.3.1}$$

where $\Delta s_{it} = s_{it} - \bar{s}_t$ and $\Delta \omega_{it} = \omega_{it} - \bar{\omega_t}$. $\bar{\omega}_t$ represents the unweighted average of mine-level productivity and $\Psi_t^{s\omega}$ is the covariance between output and productivity. The larger this covariance, the higher the reallocation effect. Table 6.4 shows that the aggregated productivity grew up by 7% from 1992 to 2010. On the one hand, the 57% of this increase can be explained by the average mine productivity growth, which was a 4% more productive in 2010 than in 1992. On the other hand, we could attribute a 43% of the increase in the aggregate productivity to the extensive margin. In other words, the aggregate productivity increased in 3% due to reallocation toward more productive mines. [3]

Finally, we find a negative correlation between price and the aggregated productivity growth (-0.28). This have two important implications. First, prices are negatively correlated with technical productivity within mines (-0.68). Second, reallocation has a negative correlation with prices (-0.81). These results are consistent with the entry (exit) of less efficient mines in periods of high (low) prices.

[3] A dynamic analysis of reallocation is left for future research. For a complete and interesting study of reallocation in the steel industry see Collard-Wexler and De Loecker (2015)

Table 6.4: Decomposition of Productivity Growth

Years	Weighted TFP: $\Delta\Omega_t$	Unweighted average: $\Delta\bar{\omega}_{it}$	Reallocation: $\Delta\Psi_t^{s\omega}$
1992-1994	0.04	0.01	0.03
1995-1997	0.00	-0.02	0.02
1997-1999	-0.01	-0.01	0.00
2000-2002	0.01	0.00	0.01
2003-2005	0.04	-0.01	0.05
2006-2008	-0.02	-0.02	0.00
2009-2010	-0.02	0.04	-0.06
1992-2010	0.07	0.04	0.03
		(0.57)	(0.43)

Note: Contribution of each component in the aggregated productivity growth in parenthesis.

7

Measuring Market Power

In this chapter, we present estimates of the competitive behaviour of the industry. First, we use aggregated data at the industry level to measure market power. We base our results on a static version of the Conjectural Variation approach. Second, we estimate the structural model and extend the analysis of market power and pricing by taking advantage of our microeconometric model developed in chapter 3 and using data at mine level. Finally, we estimate entry costs for this industry and explore its effect on price setting.

7.1 Literature Review on Conjectural Variations

The empirical estimation of market power has been widely discussed in the Industrial Organization literature. The main discussion has focused in the observability of marginal cost. This has led to two major research approaches: First, the traditional approach Structure Conduct Performance (SCP), which has been characterized by the analysis of market power based on the relationship between profit measures and industry concentration indices[1]. Second, mainly because of the unavailability of marginal cost information, it arises the New Empirical Industrial Organization (NEIO) theory, which is characterized by inferring the market behavior through price responses to variations in the elasticity of demand and exogenous cost components. NEIO models, also called Conduct Parameter Method (CPM), consist on the identification of a conduct parameter by using aggregate or firm level data[2]. CPM nests several market structures,f.i. perfect competition, collusion or others possible solutions of imperfect competition, and it reflects the markup of price over marginal costs (Karp and Perloff, 1993).

Research on conduct parameter method has spread rapidly since the pioneering work of Bresnahan (1982) and it has been widely applied in a variety of questions and industries. Among the articles that investigate market power[3], a few studies have used some static version of the CPM in commodity markets. Suslow (1986) estimates a structural model to measure the degree of market power for the interwar period in the US aluminum industry. Graddy (1995) estimates market power and price differences paid for different customers at Fulton Fish Market. Igami (2012) uses a model of demand and oligopolistic competition to assess the impact of the International Coffee cartel on prices and global welfare. Policy issues have been another area of application for the CPM. For example, Ryan (2012), using a dynamic model of oligopoly, evaluates the welfare costs of the 1990 Amendments to the Clean Air Act on the US cement industry[4].

As most of the empirical models, this approach has been exposed to several criticisms. First, Corts (1999) shows that if the conduct parameter indexing intermediate levels of collusive behavior is not the result of a conjectural variation equilibrium, then the estimated conduct parameter will tend to underestimate the degree of market power.

[1] See Perloff et al. (2007) for a book-length treatment of this subject.

[2] Bresnahan (1982) and Lau (1982) developed the necessary and sufficient conditions for identification of the conduct parameter.

[3] Bresnahan (1989) surveys the use of empirical techniques in identifying market power.

[4] See Röller and Steen (2006) and Salvo (2010) for applications of the CPM to the Norwegian and Brazilian cement industry, respectively.

As a result, the CPM would only be useful to test if the industry behaves competitively, monopolistically or à la Cournot (Zeidan and Resende, 2009). Using information of marginal cost for the US sugar industry and the British electricity spot market, Genesove and Mullin (1998) and Wolfram (1999), respectively, assess the efficacy of NEIO approach. They show that the NEIO estimations of market power are not very different to its true values.

Second, this methodology has also been questioned given its essentially static nature. For instance, if researchers estimate a static model when the firms are indeed facing a dynamic profit maximization problem, their inferences about market power will be misleading. This has given rise to explicitly model the dynamic strategic interactions between firms to measure market power. For example, Karp and Perloff (1989, 1993) use open-loop strategies assuming a particular oligopoly regimen to estimate the degree of market power in the rice and coffee export markets, respectively. Steen and Salvanes (1999) and Zeidan and Resende (2009) have estimated dynamic versions of the NEIO approach by specifying an error correction framework applied to the EU salmon and the Brazilian cement market, respectively. Kutlu and Sickles (2012) study the relationship between market power and efficiency in the US airline industry, they use a dynamic firm's profit maximization problem as base for the estimation of the conduct parameter.

Although, we acknowledge the importance of these critiques, we follow Igami (2012) and interpret the conduct parameter as the average collusiveness of the industry, which can be interpreted as a "reduced-form" representation of all the possible dynamic interactions allowing us to distinguish between different equilibrium prices.

7.2 Static Conduct Parameter

We start from the first-order condition of the firm $i's$ maximization problem:

$$P_t = MC_i\left(q_{it}, Z_t^{(s)}, \beta_i\right) - q_{it}\frac{\partial P\left(Q_t, Z_t^{(d)}, \alpha\right)}{\partial Q}\frac{\partial Q}{\partial q_i} \tag{7.2.1}$$

which can be re-written as a supply relationship:

$$P_t = MC_i\left(q_{it}, Z_t^{(s)}, \beta_i\right) + \theta_{it}\frac{P_t}{\eta_t}, \tag{7.2.2}$$

where $\eta_t = -\frac{\partial Q}{\partial P}\frac{P_t}{Q_t}$ is the price elasticity of demand, $Z_t^{(s)}$ is a vector of observable and aggregate factors that shift mine i's marginal costs. θ_{it} represents firm $i's$ conduct parameter. For example, if the firm behaves competitively then $\theta_{it} = 0$, in the case of a monopolist firm $\theta_{it} = 1$ and the Cournot oligopoly, for a symmetric n-firm, is given by $\theta_{it} = s_i = \frac{1}{n}$, where $s_i \equiv \frac{q_{it}}{Q_t}$ is the market share of firm i. Following Cowling and Waterson (1976) by using the firm $i's$ market share and summing over i, it is possible to write the industry average of firms' supply relationship in equation (7.2.2) as:

$$P_t = MC\left(Q_t, Z_t^{(s)}, \beta\right) + \theta_t\frac{P_t}{\eta_t}, \tag{7.2.3}$$

Where $MC = \sum_{i=1}^{n} s_{it} \cdot MC_{it}$ and $\theta_t = \sum_{i=1}^{n} s_{it}\theta_{it}$. θ_t still embeds perfect competition, Cournot and monopoly pricing as special cases[5] (Rosen, 2007).

7.2.1 Identification Issues

The main empirical challenge in all NEIO studies is how to identify the conduct parameter, θ. A first stage on the identification of θ is to estimate consistently the demand parameters. Then, we concentrate in the necessary assumptions to identify the demand parameters. We use $z^{(d)}$ and $z^{(s)}$ to denote representative realizations of the random variables $Z_t^{(d)}$ and $Z_t^{(s)}$. We assume that firms have prior information on the realization of the demand and marginal cost unobservables $\left(\varepsilon_t^{(d)}, \varepsilon_{\mathbf{t}}^{(\mathbf{s})}\right)$ and that the realization of $(\mathbf{q}, p)$ as a function of $\left(\mathbf{z}^{(\mathbf{d})}, \mathbf{z}^{(\mathbf{s})}, \varepsilon_{\mathbf{d}}, \varepsilon_{\mathbf{s}}\right)$ is jointly determined by firm's decision rules and the demand. This implies that price is endogenously determined. However, endogeneity can be solved with appropriate instruments for P_t, for which the cost covariates, $Z_t^{(s)}$, are reasonable candidates. Instrumental variable estimations for lineal models is

[5] See Appendix B.1 for the detailed derivation of the conduct parameter and its special cases.

well known, then we present assumptions for the demand identification as:

Assumption 1. *Each component of* $(\mathbf{q}, p)$ *has nonnegative bounded support.*

The exclusion restriction to estimate the demand function independently of the marginal cost function is given by:

Assumption 2. $\mathbb{E}\left[\varepsilon_t^{(d)}, \varepsilon_{\mathbf{t}}^{(\mathbf{s})} | Z^{(d)}, Z^{(s)}\right] = 0$

The intuition behind this assumption is that the demand is a function of exogenous variables affecting the demand but not the marginal costs and viceversa. Moreover, we treat the inverse demand function and its derivative with respect to Q as observed.

Assumption 3. $P\left(Q, Z^{(d)}\right)$ *is continuously differentiable in* Q *and* $\frac{\partial P\left(Q, Z_t^{(d)},\right)}{\partial Q} < 0$ *for all* $z^{(d)} \in Z_t^{(d)}$.

The estimation process of the demand parameters is the base for the estimation of θ. However, the identification procedure will depend on the information on the marginal costs known by the researcher. Firstly, if the researcher has full information on marginal costs, Genesove and Mullin (1998) propose a direct measure of the conduct parameter or elasticity-adjusted Lerner index. Then, with full information on marginal cost and solving for θ_t in equation (7.2.3), the conduct parameter can be written as:

$$\begin{aligned} \theta_t &= \frac{P_t - MC(\cdot)}{P_t} \cdot \eta_t \\ &= L_t \cdot \eta_t \end{aligned} \tag{7.2.4}$$

where L_t is the Lerner index, so that θ_t is an elasticity-adjusted Lerner index. Note that, in the case of an industry facing an inelastic demand, the elasticity-adjusted Lerner index will be lower than the unadjusted Lerner index, whereas for a monopoly, that always produces on the elastic region of the demand curve, it will be higher. Secondly, in the case that the researcher had incomplete information on marginal costs, the identification procedure differs according to the knowledge on the functional form of marginal costs. Bresnahan (1982) propose to modify the demand equation by adding interaction terms between price and demand shifters.[6]

[6] Interested readers are referred to Bresnahan (1982) for an illustration of the identification procedure

7.2.2 Estimation of the Static Model

In this section, we present estimates of the static model of conjectural variations. The estimation follows in two steps. In a first step, we estimate the parameters of the demand function. In a second step, we estimate the conduct parameter by both the direct and NEIO approaches using industry level data and estimates of the demand.

7.2.3 Demand

Demand estimation provides the basis for the subsequent discrete and dynamic analysis. We use a linear specification as a starting point. Since copper is an homogenous good, its demand is a derived demand without any identification of the producer. Copper is mainly used in the production of intermediate goods which are later used as inputs in the production of final goods. Table 7.1 presents the estimates of the demand parameters based on the following linear form:

$$Q_t = \alpha_0 + \alpha_1 P_t + \alpha_2 GDP_t + \alpha_3 PAl_t + \alpha_4 P_t \times PAl_t + \varepsilon_t^{(d)} \tag{7.2.5}$$

where Q is the world copper consumption, P_t is the LME copper price, GDP_t is the importing countries' GDP, PAl_t is the price of aluminium, and $\varepsilon_t^{(d)}$ is the unobserved shock for the demand.

when partial information is available.

Table 7.1: Demand Estimates

	OLS			IV		
Dependent var: Q_t	[1]	[2]	[3]	[4]	[5]	[6]
P_t (Copper price)	-16.82	-6.98	-55.55***	-20.32	-9.96**	-114.87***
	(11.37)	(5.64)	(16.52)	(12.40)	(4.97)	(36.38)
GDP		0.36***	0.35***		0.37***	0.36***
		(0.04)	(0.03)		(0.04)	(0.03)
Aluminium price		2.93	-76.01***		7.20	-165.77***
		(9.42)	(21.18)		(10.12)	(49.74)
$P_t PAl_t$ (Interaction)			0.42***			0.91***
			(0.13)			(0.29)
Constant	9601.65***	2650.29*	11547.73***	9000.62***	2247.59	21722.57***
	(2269.45)	(1466.60)	(2276.89)	(2455.56)	(1743.43)	(5988.17)
Adjusted R^2	0.12	0.90	0.91	0.11	0.89	0.88
Overid				5.00	4.94	5.06
p-value				0.08	0.08	0.08
η_P (Price elasticity)	-0.23	-0.10	-0.11	-0.28	-0.14	-0.16
η_{PZ} (Cross-price elasticity)		0.03	-0.04		0.07	-0.08

In table 7.1, columns [1], [2] and [3] present the OLS estimates. In columns [4], [5] and [6], to address the potential simultaneity problem, we apply two-stage least squares using the (aggregated) variables Wages, Energy and a time trend as instrument for price. Demand estimates look reasonable, the income variables present positive coefficients and most of coefficients are significant at 5 percent level. The cross-price elasticity at the point of means is $\eta_{P \times PAl} = \left[\alpha_3 + \alpha_4 \overline{P}\right] \left[\frac{\overline{PAl}}{\overline{Q}}\right]$ are between -0.04 and -0.08. We would have expected a positive cross-price elasticity. However, several author have presented similar results. Fisher et al. (1972b) states that this can be explained because the aluminium price is not an equilibrium price because it is subject to discounts and quantity rationing. The same author proposes that the most common solution is to use aluminium prices from a competitive market such as Germany. However, we have not access to this data and we decided to keep the LME aluminium price in the model even if the results are mixed.

Now, we focus our attention on price elasticity. As expected, IV estimates are more stable and higher in magnitude than OLS. This is because the instruments, energy and wages, isolate both the unobserved demand shocks and the noise due to measurement error. The p-values of the Hansen test for over-identifying restrictions do not reject the validity of the instruments. Given that an inconsistent or biased estimation of price elasticity would lead to misleading interpretations on the industry's market conduct θ, it would be desirable that our estimated elasticity were similar to the ones observed in the literature. Fisher et al. (1972b) estimated separately demand equations for the United States, Europe, Japan and the rest of the world in the period between 1950 and 1966, where the estimated price elasticities, in absolute values, were 0.21, 0.08, 0.09 and 0.22, respectively. Taking weighted average, the price elasticity were 0.15 [7]. Using a linear model and monthly data in the 1950 - 1995 period, Agostini (2006) estimated the price elasticity for the United States in the range from 0.12 to 0.24, in absolute values. Therefore, a comparison of price elasticities in table 7.1 with these estimates show that our results are no far from these authors' findings.

As a simple back of the envelope calculation, we estimate the monopoly and Cournot pricing rules using the elasticity price in column $[4]$[8]. The mean monopoly price would be $\$330.43$, well above the observed mean price of $\$153.09$ in table 4.1, while that the Cournot price would be $\$133.72$, 12% below the observed mean price[9]. These results foreshadow some of the final findings of this chapter.

7.2.4 Direct Measures of the Conduct Parameter

In this section, we use as benchmark for the conduct parameter its estimated value considering the full set of available information and the elasticity of demand, η, recovered from the previous section. Although, we do not know the marginal cost as precisely, we use the information of the direct cash costs as a proxy. Then, we estimate the con-

[7] The weights being proportional to 1963 consumption as published in Fisher et al. (1972b) and using annual data.

[8] See Appendix B.2 for a detailed derivation of these prices.

[9] Price estimated with a ten-firm symmetric Cournot oligopoly.

duct parameter by the elasticity adjusted Lerner index, L_η in equation (7.2.4). Table 7.2 presents summary statistics of this measure. The first row shows the well-known Lerner index while that in the subsequent rows, we present the adjusted Lerner index with the elasticities taken from the corresponding demand specification in table 7.1.

Table 7.2: Estimates of the Conduct Parameter

Lerner Index	Mean	Std. Dev.	Std. Error	95% Conf. Interval	
Unadjusted:	0.42	0.17	0.03	0.36	0.49
Adjusted using specification:					
[1]	0.10	0.04	0.01	0.08	0.11
[2]	0.04	0.02	0.00	0.03	0.05
[3]	0.05	0.02	0.00	0.04	0.05
[4]	0.12	0.05	0.01	0.10	0.14
[5]	0.06	0.02	0.00	0.05	0.07
[6]	0.07	0.03	0.00	0.06	0.08

The price-cost markup in this industry is sizable, yet the measured conduct parameter, θ, is very small. The first row indicates that the price is 42% higher than the producer's marginal costs, while that the mean L_η is close to 0.07. In the case of the IV specifications the mean is close to 0.08. This implies a level of competition similar to a static Cournot oligopoly with 14 and 12 symmetric firms, respectively. This is a similar structure to the one presented in table 4.2. The small values of the conduct parameter are mainly explained by the inelasticity of the demand. Based on this results, we can clearly reject both hypothesis competitive pricing $(\theta = 0)$ and and the monopoly pricing $(\theta = 1)$.

Though the high price-cost markup seems the result of a more collusive regime, the producers appear not to be taking full advantage of the inelasticity of the demand to charge even higher prices. A reasonable initial explanation is that the industry pricing behavior was constrained by the substitution effect of aluminum. As mentioned before, a high long run price of copper can lead to a material substitution process[10]. Overall, given these results there is evidence to reject both perfect competition and monopoly behavior. In addition, the Cournot equilibrium seems the most likely result for this industry.

7.2.5 Static Conjectural Variation Estimates

In this section, we present the results of the conduct parameter estimations using the NEIO or conjectural variations approach. We identify θ by analyzing the producer's response to changes in demand following the oligopoly model formulated by Bresnahan (1982) and Lau (1982). This method allows for a more flexible structure about the functional form of the marginal costs. We assume constant and increasing functional forms for the marginal cost function when estimating the conduct parameter.

Taking into account these two forms of marginal costs, the supply relationship can be written in an empirical form as:

$$P_t = \beta_0 + \beta_1 Q_t + \beta_2 W_t + \beta_3 En_t + \theta Q_t^* + \varepsilon_t^s \tag{7.2.6}$$

where W_t represents wages, En_t is the energy price and $Q^*_= - \frac{Q_t}{(\alpha_1 + \alpha_3 PAl_t)}$. When assuming constant marginal cost, β_1 in the supply relationship is zero and it is not necessary for identification the interaction term in the demand equation Perloff et al. (2007). In the case of increasing marginal costs, we use the classic procedure of Bresnahan (1982) and Lau (1982).

Table 7.3 presents the estimates of the supply relationship assuming both functional forms for the marginal costs.[11] The Hansen J statistics for overidentification tests sup-

[10] Although substitution effect results are mixed in the demand estimation, this effect should be considered and analyzed with a long run elasticity. For a complete analysis of the copper-aluminum substitution see Messner (2002).

[11] We experimented with several estimations being the main difference the variables used to measure energy and wage, our preferred estimates were using oil prices and mine wages as measure of energy and

port the validity of the instruments. Coefficient estimates of the conduct parameter, θ, range between 0.35 and 0.0012. As before, we can reject perfect competition and monopoly power. However, these results are fare from the benchmark conduct measured value reported in table 7.2 (0.06 and 0.07 respectively).

The difference in the estimates of θ seems to suggest that the identification of the conduct parameter is very sensitive to assumptions of the functional form in the marginal cost function. On the one hand, by assuming constant marginal costs the conduct parameter is upwards biased. The source of this bias could be an omitted variable bias as quantity appears to be a key component of the supply relationship. On the other hand, when we assume increasing marginal costs, the conduct parameter is underestimated. Thus, even when it is unclear to what extent it is possible to apply NEIO techniques to the international copper industry, this method at least allows to reject both perfect competition and monopoly pricing.[12]

wage respectively.

[12] Similar results were obtained by Genesove and Mullin (1998) and Wolfram (1999) using increasing marginal costs.

Table 7.3: Supply Relationship

	Marginal costs	
Dependent var: P_t	[5]	[6]
	Constant	Increasing
W_{1t} (Wage)	0.4201***	0.4038***
	(0.0448)	(0.0387)
W_{2t} (Energy)	0.8646***	1.0374***
	(0.3121)	(0.3058)
Q_t (Consumption)		0.0346***
		(0.0031)
Constant	-1405.0626***	-1362.2021***
	(149.5899)	(130.7689)
θ Conduct parameter	0.3547***	0.0012***
	(0.0343)	(0.0002)
Adjusted R^2	0.7478	0.7662
Overid	4.1580	3.4483
p-value	0.1251	0.1783

7.3 Estimation of the Structural Model

This section presents the estimates of our theoretical model developed in chapter 3. We proceed in two steps. In the first step, we estimate a dynamic model of conjectural variations using the euler equation (3.2.1). Second, we estimate the parameters in the fixed and entry cost functions using the discrete euler equation (3.2.11).

7.3.1 Dynamic Conduct Parameter

In this section, we provide a microeconometric dynamic analysis of the level of competition in this industry. We extend the Static Conjectural Variation approach by estimating a dynamic model of competition taking advantage of the Euler equation for output from our theoretical model in chapter 3:

$$MR_t - MC_t = \beta\, \mathbb{E}_t \left([MR_{t+1} - MC_{t+1}]\, \frac{(1+q_{t+1})}{(1+q_t)} + \alpha_g \delta_q^{(g)} \frac{q_{t+1}}{(1+q_t)} MC_{t+1} \right) \tag{7.3.1}$$

The dynamic in this model comes from the expectations of price and marginal cost in the next period as well as the expected depletion effect, $\alpha_g \delta_q^{(g)} \frac{q_{t+1}}{(1+q_t)} MC_{t+1}$. As mentioned before, the depletion effect measures the impact on future marginal costs from exploiting the mine today. Given the form of the Euler equation, we can explore the nature of competition at mine and firm level in a static and dynamic framework and to measure the impact of the depletion effect on competitive behavior by applying the Conjectural Variation approach to the Euler equation 7.3.1.[13] We first consider competition at mine level. An empirical model to test for competition based in our Euler equation can be written as:

i) Static model:

$$P_t - MC_{it} = \tilde{\theta}^M P_t \frac{q_{it}}{Q_t}$$

ii) Dynamic model without depletion effect:

$$P_t - MC_{it} - \beta \left(P_{t+1} - MC_{it+1} \right) \frac{(1+q_{it+1})}{(1+q_{it})} = \tilde{\theta}^M \left(P_t \frac{q_{it}}{Q_t} - \beta P_{t+1} \frac{q_{it+1}}{Q_{t+1}} \frac{(1+q_{it+1})}{(1+q_{it})} \right)$$

[13]Static in this model refers to shut down the marginal effect on next period profits.

iii) Dynamic model with depletion effect:

$$P_t - MC_{it} - \beta \left[(P_{t+1} - MC_{it+1}) \frac{(1+q_{it+1})}{(1+q_{it})} + \alpha_g \frac{q_{it+1}}{(1+q_{it})} \delta_q^{(g)} MC_{it+1} \right] =$$
$$\tilde{\theta}^M \left(P_t \frac{q_{it}}{Q_t} - \beta P_{t+1} \frac{q_{it+1}}{Q_{t+1}} \frac{(1+q_{it+1})}{(1+q_{it})} \right)$$

where $\tilde{\theta}^M = \left(\frac{1+\theta^M}{\eta_D}\right)$, θ^M is the conduct parameter at mine level and η_D is the elasticity of demand (estimated in section 7.2.3). The value of the conduct parameter, as before, captures the competitive behavior in the industry, f.i. competitive pricing, $\theta^M = -1$, Cournot pricing, $\theta^M = 0$, or the cartel pricing with symmetric mines, $\theta^M = N - 1$.[14] By including mine fixed effects, we can address the Corts' critique of tacit collusion as suggested by Puller (2009). The top panel in Table 7.4 presents estimates of the conjectural variation at mine level for the static, dynamic and dynamic including depletion effect models. Standard errors of the conduct parameters are computed through the Delta method. The fixed effect estimates of the conduct parameter, in columns (1) to (3), are between -0.73 and 10.18. The static model predicts a very competitive structure while that the dynamic models present a structure something less competitive that the Cournot solution.

Given that the right hand side in our Euler representations of the conjectural variation model could be endogenously determined, as prices and quantities are simultaneously driven, we also estimate them by IV-GMM in columns (4) - (6). The Conduct parameters are now less competitive in all the models, ranging from 9.72 in the static model to 47.53 in the dynamic model including depletion. These results clearly reject both perfect competition and the joint profit-maximization solution. Moreover, the depletion effect seems not to play an important role in the degree of competition, as the difference between the dynamic model with and without depletion effect is very small. In other words, the natural depreciation due to exploitation is a common factor across mines and it is already internalized in the definition of the competitive strategies of mines.

Similarly, the flexibility of the Euler equation allows us to explore competition at

[14] Note that values of conjectural variation in the dynamic model differ from the static one.

firm level. Unlike the previous analysis, mines belonging to the same firm are managed by a general manager. Therefore, we assume that this firm manager maximizes the joint profit of all mines within the firm. We can write an empirical model of conjectural variations at firm level as:

i) Static model:

$$P_t - MC_{it} = \tilde{\theta}^F P_t \frac{Q_{f(i)t}}{Q_t}$$

ii) Dynamic model without depletion effect:

$$P_t - MC_{it} - \beta \left(P_{t+1} - MC_{it+1}\right) \frac{(1+q_{it+1})}{(1+q_{it})} = \tilde{\theta}^F \left(P_t \frac{Q_{f(i)t}}{Q_t} - \beta P_{t+1} \frac{Q_{f(i)t+1}}{Q_{t+1}} \frac{(1+q_{it+1})}{(1+q_{it})} \right)$$

iii) Dynamic model with depletion effect:

$$P_t - MC_{it} - \beta \left[\left(P_{t+1} - MC_{it+1}\right) \frac{(1+q_{it+1})}{(1+q_{it})} + \alpha_g \frac{q_{it+1}}{(1+q_{it})} \delta_q^{(g)} MC_{it+1} \right] =$$
$$\tilde{\theta}^F \left(P_t \frac{Q_{f(i)t}}{Q_t} - \beta P_{t+1} \frac{Q_{f(i)t+1}}{Q_{t+1}} \frac{(1+q_{it+1})}{(1+q_{it})} \right)$$

where $\frac{Q_{f(i)t}}{Q_t}$ represents the market share of the firm f to which mine i belongs to. $\tilde{\theta}^F = \left(\frac{1+\theta^F}{\eta_D}\right)$ and θ^F is the conduct parameter at firm level. Similar results to the analysis at mine level are obtained for competition at firm level in the middle panel of table 7.4, although estimates of the conduct parameter are lower than the ones at mine level. Moreover, estimates are very close to the Cournot solution.

Finally, the theoretical model allows us to understand the relevant unit level of competition f.i. mine or firm level. We can nest several regimes of competition such as Cournot or perfect competition at mine and firm level in a single general model and test for which unit better explain the data. For example, in the case of a dynamic model with depletion, the nested or general model of competition can be written as:

$$P_t - MC_{it} - \beta\left[(P_{t+1} - MC_{it+1})\frac{(1+q_{it+1})}{(1+q_{it})} + \alpha_g \frac{q_{it+1}}{(1+q_{it})}\delta_q^{(g)} MC_{it+1}\right] =$$
$$\tilde{\theta}^{NM}\left(P_t\frac{q_{it}}{Q_t} - \beta P_{t+1}\frac{q_{it+1}}{Q_{t+1}}\frac{(1+q_{it+1})}{(1+q_{it})}\right) + \tilde{\theta}^{NF}\left(P_t\frac{Q_{f(-i)t}}{Q_t} - \beta P_{t+1}\frac{Q_{f(-i)t+1}}{Q_{t+1}}\frac{(1+q_{it+1})}{(1+q_{it})}\right)$$

where the regime of competition would be:

a) An oligopoly solution at firm level if $\tilde{\theta}^{NM} = \tilde{\theta}^{NF} > 0$

b) An oligopoly solution at mine level if $\tilde{\theta}^{NM} > 0$ and $\tilde{\theta}^{NF} = 0$

c) Cournot solution at firm level if $\tilde{\theta}^{NM} = \tilde{\theta}^{NF} = \frac{1}{\eta_D}$

d) Cournot solution at mine level if $\tilde{\theta}^{NM} = \frac{1}{\eta_D}$ and $\tilde{\theta}^{NF} = 0$

e) Perfect competition if $\tilde{\theta}^{NM} = \tilde{\theta}^{NF} = 0$

Table 7.4: Conjectural Variation Estimates

	Mine Level					
	Fixed Effect			**IV-GMM**		
Variable	Static	Dynamic	Depletion	Static	Dynamic	Depletion
$\tilde{\theta}^M$	0.8961*	36.8807***	37.2734***	35.7286***	158.8657***	161.7532***
	(0.493)	(4.948)	(4.986)	(5.112)	(18.448)	(18.786)
Constant	1159.7732***	36.1302	10.4365	3166.0799***	-223.1199	-237.5774
	(73.253)	(213.069)	(214.656)	(346.657)	(1148.835)	(1169.881)
Number of Obs.	1864	1864	1864	1864	1864	1864
θ^M	-0.7312	10.0642	10.1820	9.7186	46.6597	47.5260
	(0.1479)	(1.4844)	(1.4959)	(1.534)	(5.534)	(5.636)
Hansen p-value	-	-	-	0.0000	0.3213	0.3157
	Firm Level					
	Fixed Effect			**IV-GMM**		
Variable	Static	Dynamic	Depletion	Static	Dynamic	Depletion
$\tilde{\theta}^F$	0.7196***	6.8985***	7.0262***	11.2211***	20.8877***	21.2750***
	(0.238)	(1.127)	(1.116)	(1.838)	(1.814)	(1.839)
Constant	1375.5509***	564.9152***	548.7357***	2801.1761***	-534.2012	-553.987
	(78.058)	(142.748)	(141.941)	(390.478)	(817.197)	(828.604)
Number of Obs.	1864	1864	1864	1864	1864	1864
θ^F	-0.7841	1.0695	1.1079	2.3663	5.2663	5.3825
	(0.072)	(0.338)	(0.335)	(0.551)	(0.544)	(0.552)
Hansen p-value	-	-	-	0.0000	0.0002	0.0002
	Nested Model					
	Fixed Effect			**IV-GMM**		
Variable	Static	Dynamic	Depletion	Static	Dynamic	Depletion
$\tilde{\theta}^{NM}$	0.4569	28.7139***	28.8933***	34.4128***	131.2138***	133.2582***
	(0.511)	(5.134)	(5.156)	(6.749)	(37.449)	(38.043)
$\tilde{\theta}^{NF}$	0.7709***	4.6916***	4.8141***	1.1709	3.9094	4.0424
	(0.289)	(0.448)	(0.448)	(3.423)	(6.203)	(6.302)
Constant	1367.6997***	-55.3711	-83.4545	3083.2807***	-295.0495	-311.2214
	(81.282)	(185.069)	(185.733)	(406.534)	(977.348)	(992.847)
Number of Obs.	1864	1864	1864	1864	1864	1864
θ^{NM}	-0.8629	7.6142	7.668	9.3238	38.3641	38.9775
	(0.153)	(1.540)	(1.547)	(2.025)	(11.235)	(11.413)
θ^{NF}	-0.7687	0.4075	0.4442	-0.6487	0.1728	0.2127
	(0.087)	(0.134)	(0.134)	(1.027)	(1.861)	(1.891)
$H_0 : \tilde{\theta}^{NM} = 0$	0.3715	0.0000	0.0000	0.0000	0.0005	0.0005
$H_0 : \tilde{\theta}^{NF} = 0$	0.0076	0.0000	0.0000	0.7323	0.5286	0.5212
Hansen p-value	-	-	-	0.0000	0.1035	0.1001

Note: Dependent variable is left hand side in each model. Explanatory variables are defined as the right hand side (rhs) in each model. β fixed at 0.95. All regressions include time and mine dummies.

The bottom panel in table 7.4 presents estimates of the static, dynamic and dynamic with depletion nested models. We present estimates for both fixed effects and Instrumental Variables GMM. The fixed effect results suggest a more competitive environment in all specifications. The IV-GMM estimates show a significative value for the parameter of competition at mine level, $\tilde{\theta}^{NM}$, while that the associated firms' conduct parameter $\tilde{\theta}^{NF}$ is not significative. Therefore, we cannot reject the null hypothesis of $\tilde{\theta}^{NM} > 0$ and $\tilde{\theta}^{NM} = 0$, this suggest that strategic interactions between mines explain better the competition in this industry. This is an important result because it suggests that given the substantial heterogeneity across mines even within a firm, managers will set its level of output and strategies taking into account strategies of rival mines rather than rival firms. This is a more reasonable result for large and medium mines because to shut down temporarily a mine is costly. The results also suggest an environment something less competitive than Cournot, $\theta^{NM} \in \{9, 39\}$. In general, these results provide reasonably evidence of market power and strategic behavior in this industry. However, results of the conduct parameters are constant over time and not take into account short-run changes in the competitive behavior, so they should certainly be read carefully.

7.3.2 Price Counterfactual Experiments

In the above section, we have exploited our continuous Euler equation to study the competitive behavior in the copper industry. With the same structure and taking advantage of the richness of the data, we can perform a simple experiment to study the effect of both market power and depletion effect on price. Copper price is highly volatile and uncertain, it decreased by more than 20% between the years 1992 and 2000 and increased in almost 3 times in 2008. In our experiment, if we shut down market power the copper price would have been, in average, a 19% lower. However, the hypothetical price without market power and the actual price follow the same trend, so market power cannot explain by itself the volatility of prices. As described before, this trend is mainly determined by the demand of developing countries. Second, we analyse the influence of the depletion effect on copper prices. Results suggest that without depletion effect the price of copper would have been, in average, 1,3% lower than the actual price. This is a non-negligible effect, taking into account that the average mine in the sample produce 147 thousand tons of copper per year, this would imply an average decrease in incomes of 6 million dollars per year. However, as in the case of market power, it is not enough to explain the high volatility of prices. Table 7.5 shows the actual and hypothetical prices from this exercise.

Table 7.5: Hypothetical Prices: No Market Power and No Depletion Effect

	Copper Price					
Year	Actual	%	No Market Power	%	No Depletion	%
1992	2299.21	-	1921.76	-16%	2269.60	-1.30%
2000	1812.20	-21%	1435.58	-21%	1785.92	-1.50%
2008	6950.95	284%	5402.37	-22%	6880.31	-1.01%

7.3.3 Entry Cost Estimates

In this section, we estimate the structural parameters in the entry and fixed cost functions, $\theta = \{C^{(e)}, \theta_i^{(fc)}, \sigma_\varepsilon\}$ for $i = 1, ..., 4.$, derived in the section 3.2.2 using a two-step GMM estimator. The first step consists in the estimation of the conditional choice probabilities (CCPs) at two consecutive periods, $P_t(a_{it+1}|\mathbf{x_{it}})$ and $P_{t+1}(a_{it+2}|a_{it+1}, \mathbf{x_{it+1}})$, $\forall \;\; a_{it}, a_{it+1} \in \{1, 0\}$. We estimate the decision of being active next period using a logit model and including all the state variables as regressors:

$$\begin{aligned} P_t(a_{t+1} = 1|\mathbf{x_t}) \;\;&=\;\; \Lambda(\beta_0 + \beta_1 P_t + \beta_2 g_{it} + \beta_3 r_{it} + \beta_4 \omega_{it} \\ &\quad + \beta_5 k_{it} + \beta_7 p_{it}^l + \beta_8 p_{it}^e + \beta_9 p_{it}^f + \beta_{10} Q_{-it} + \beta_{11} a_{it} + e_{it}) \end{aligned} \tag{7.3.2}$$

Given that individual state variables are not observable for potential entrants, we estimate them by running an OLS regression of the state variable on a fixed effect and a time dummy, $s_{it} = \alpha_i + \gamma_t + \varepsilon_{it}$[15]. Given this representation of the conditional choice model, the estimated probability that a mine is active in the next period conditional on the state variables $\mathbf{x_{it}}$ is:

$$P_t(\widehat{a_{t+1} = 1}|\mathbf{x_t}) = \frac{exp\{\mathbf{X'}\hat{\beta}\}}{1 + exp\{\mathbf{X'}\hat{\beta}\}} \tag{7.3.3}$$

In the second step, we estimate our parameterized Euler equation[16]:

$$\begin{aligned} \beta \left[VP^*(\mathbf{x_{t+1}}) - p^k_{it+1}k_{it+1}\right] &= -\beta C^{(e)}(\mathbf{x_{t+1}}) + (1 - a_t)C^{(e,x)}(\mathbf{x_t}) \\ &+\theta_1^{(fc)}\beta k_{it+1} + \theta_2^{(fc)}\beta r_{it+1} + \theta_3^{(fc)}\beta k^2_{it+1} + \theta_4^{(fc)}\beta r^2_{it+1} + \sigma_\epsilon\widetilde{\varepsilon}_{t+1} \end{aligned} \tag{7.3.4}$$

where $VP^*(\mathbf{x_{t+1}}) = P_{t+1} \times q_{it+1}(\mathbf{x_{t+1}}) - VC_{it+1}(\mathbf{x_{t+1}})$ and $\widetilde{\varepsilon}_{t+1} = [\ln(1 - P_t(1|\mathbf{x_t})) + \beta \ln P_{t+1}(1, 0, \mathbf{x_{t+1}}) - \ln P_t(1|\mathbf{x_t}) - \beta \ln P_{t+1}(1, 1, \mathbf{x_{t+1}})]$.

We estimate $\theta = \{C^{(e)}, C^{(e,x)}, \theta_i^{(fc)}, \sigma_\varepsilon\}$ using a GMM estimator based on the moment condition $E_t(Z_t\{VP^*(\mathbf{x_{t+1}}) - p^k_{it+1}k_{it+1} - \theta_1^{(fc)}\beta k_{it+1} - \theta_2^{(fc)}\beta r_{it+1} - \theta_3^{(fc)}\beta k^2_{it+1} - \theta_4^{(fc)}\beta r^2_{it+1} + \beta C^{(e)}(\mathbf{x_{t+1}}) - (1 - a_t)C^{(e,x)}(\mathbf{x_t}) - \sigma_\epsilon\widetilde{\varepsilon}_{t+1}\})$, where the vector of instruments Z_t is $\{1, g_{it-1}, \ln P(1|\mathbf{x_t})\}'$[17].

[15] We consider as potential entrants, mines which were active in any period of the sample. Similar results are also obtained for the predicted choice probabilities if we keep equal to the last available observation the values for the deterministic state variables, $\{g_{it}, r_{it}\}$.

[16] Given that is not possible to identify separately $C_i^{(e)}(X_t)$ from $C_i^{(x)}(X_t)$ in equation (3.2.11), the parameter $C^{(e,x)}$ provides a net (of the exit value) entry cost. An alternative method to avoid this constraint is to estimate a Pseudo Likelihood Policy Iteration mapping for the Euler equation (EE-PI), where the dependent variable would be the choice probability.

[17] The entry indicator is treated as endogenous.

Table 7.6: Estimation of Entry Costs

	(1) OLS	(2) IV-GMM
$C^{(e,x)}(\mathbf{x_t})$	4434561.8747***	4015409.0413***
	(351692.704)	(468787.228)
$\theta_1^{(fc)}$	2511.4382***	2653.4407***
	(357.998)	(372.327)
$\theta_2^{(fc)}$	-0.3240***	-0.3292***
	(0.085)	(0.085)
$\theta_3^{(fc)}$	-3.2100***	-2.9004***
	(0.378)	(0.442)
$\theta_4^{(fc)}$	0.0000**	0.0000***
	(0.000)	(0.000)
σ_ε	-829753.4801***	-755549.5284***
	(63962.473)	(84268.385)
$\beta C^{(e)}(\mathbf{x_{t+1}})$	-4265633.1874***	-3878864.9085***
	(332862.473)	(438830.180)
Obs.	1132	1132
R^2	0.6286	0.6281

Table 7.6 presents estimates of the structural parameters based on the Euler equation 7.3.4. The annual discount factor, β, is fixed at 0.95. All the estimated parameters are measured in 2010 thousands of dollars. The estimated entry cost is roughly 3.8 billions of dollars. For comparison reasons, it is helpful to take into account that the annual revenue generated by the average mine is 624.25 millions of dollars. The mean value of the annual variable profit is approximately 496.4 millions of dollars whereas that the average estimated fixed cost is 113.7 millions of dollars. Therefore, the estimated entry cost represents 7.8 times the annual variable profits and 34 times the fixed costs. The average mine in the sample takes almost 10 years to recover its initial investment. The

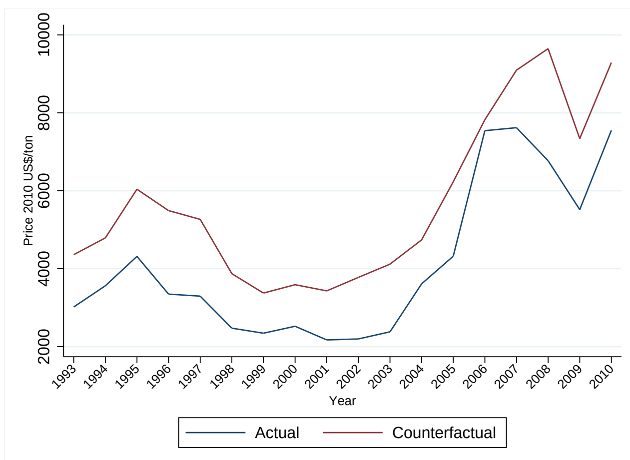
average life of a mine is 32 years in our sample[18], this implies an internal rate of return of 9%. Given our representation of the Euler equation, we can recover the exit value as the difference between $\beta C^{(e)}(\mathbf{x_{t+1}})$ and $C^{(e,x)}(\mathbf{x_t})$. This implies a non-negligible exit value of 136.5 millions of dollars for the average mine. It is interesting to note that the exit value implies an important cost for the mine and it can be associated with a cost of closure due to environmental regulation[19]. Finally, the low value of the ratio between the means of the average cost (\$2435.1 /t) and the marginal costs (\$1137.8) suggests substantial economies of scale for this industry. However, the coefficients of capital implies a concave relationship between capital and the profit measure suggesting that there is an optimal size of the mine to exploit this economies of scale.

Finally, we use the estimates of the structural parameters to conduct a counterfactual experiment by quantifying the effect of the entry cost on the price evolution. Figure 7.1 shows the actual and the estimated price due to an increase of 10% in the entry costs. In average, an increase of 10% on entry costs will lead to an increase of 43% in the price.

[18]The sample in this section is reduced from 1864 to 1132 observations due to missing values for the cost of capital.

[19]Typically in dynamic games, exit implies a positive revenue for firms as they sell their infrastructure to other firms or as scrap metal. However, closing a mine could be a complex process, it requires to remove large infrastructures and equipment, the rehabilitation of the environment and a permanent monitoring of the toxic waste generated during its operation. This process could last several years or even decades and it is subject to a strict regulation in some producer countries.

Figure 7.1: Counterfactual Experiment: Increase in Entry Costs.



8

Conclusion

This thesis have explored the microeconometrics of the world copper mining industry. It makes a contribution to both the industrial organization literature and the natural resources literature by proposing and estimating a dynamic structural model that includes several characteristics of this industry that have been omitted by previous econometric models using data at more aggregate level. We have build a unique dataset of almost two decades for 330 mines in this industry. This also is an important empirical contribution. The dataset contains information provided by one of the world's largest copper producers and data collected from other several private and public sources. The dataset includes detailed information on price, capacity, production, reserves, ore grades, input uses and prices, opening and closing activity and other characteristics at mine level.

In this thesis, important drivers of the supply of copper are identified and outlined. First, there is a large heterogeneity in geological characteristics across mines that helps to understand the dynamics of the market structure. It is found that differences in ore grade is the main determinant of heterogeneity in marginal costs. If it were possible to eliminate the heterogeneity in ore grade, keeping all other elements constant, the variance of marginal costs would decline by almost 60%. These exogenous or natural differences also help to explain entry and exit decisions. It is found evidence of a substantial number of mines in the lower part of the distribution of ore grades that adjust their production at the extensive margin, i.e., temporary mine closings and re-openings, in response to price changes. There is also strong evidence of changes at the intensive margin in response to price changes, f.i., mines increase the extraction of lower quality ores, increasing their marginal costs, when price is high.

Second, it is found an important depletion effect. Natural endowments at mine level such as ore grades and reserves are not constant over time and they evolve endogenously. Ore grades decline with the depletion of mine reserves, and they may increase as a result of investment in exploration within the mine. Doubling today's output implies a 7% reduction in mine productivity next period. There is evidence of almost a one-to-one relationship between ore grades and marginal costs, the depletion effect of ore grades represents, in average, 5% of marginal costs. It is important to note that this thesis is the first attempt into introduce theoretically and empirically the endogeneity of ore grades.

Third, results from the production function estimates have shown evidence of constant returns to scale and substantial economies of scale. It is also found that production technology in this industry is very energy and capital intensive. This supports the idea that mining can be thought as a modern industry where massive and relatively low-grade ores are exploited by highly skilled workers and using modern equipment and technology. On the other hand, there is evidence of a positive productivity growth and that this growth could be explained in part by reallocation of resources from less to more productive mines.

Fourth, results from the output Euler equations estimates provide strong evidence of market power and strategic behaviour. Descriptive evidence also showed that the concentration ratio of the four largest mines was more than 26% and the average Lerner index was 42%, this is a suggestive indicator for the possibility of market power. Conjectural variation estimates reject both a competitive and monopolistic behaviour and suggest that the Cournot model of oligopoly could explain better the data. This is an important result as the literature of natural resources typically assumes that commodity markets behaves competitively. Counterfactual experiments showed that market power plays an important role in determining the structure of the industry, f.i., by eliminating market power, price would decrease, in average, by almost 20%.

Finally, structural estimates show that mines have to pay substantial sunk entry and exit costs. For example, estimates indicate that, in average, the entry cost can reach 3.8 billions of dollars while that exit costs are almost 140 millions of dollars. These sunk costs represent an important barrier to entry and help to explain the large concentration and market power in this industry. In addition, the conducted experiments have shown that start-up costs are an important determinant of price setting, f.i., an increase of 10% in the entry cost would imply an increase of almost 40% in the average price.

Finally, an interesting extension of this work would be to include investment in capacity, measured as capital and equipment investments, in the model. These investment decisions could be important for the structure of the industry, f.i., incumbent mines could adjust their capacity by both responding to demand shocks or strategically reasons to prevent entry. This extension is currently being explored in a working paper that include most of the findings of this thesis. Further extensions of this thesis include to explore the effects of an increasing environmental regulation in extractive industries and recent technological breakthroughs in mining on productivity and the market structure. Among the main findings in this thesis, it has been highlighted that the exit value or closing cost could play an important role in mines' decision of remain active and that environmental costs of closing would be an important component of this closing costs. Therefore, environmental regulation could have important consequences on price and market power in this industry. On the other hand, copper mining has experimented recent developments in production technology such as the introduction of the electrowinning technique. One question that could be addressed is weather improvements in technology have played a role in the observed productivity growth. There are many other interesting dynamic features in this industry to explore, from the substantial number of merges and acquisitions observed in the data to the dynamics in demand and inventories. All these interesting topics are leaved for future work.

The results provided in this thesis help to understand better the dynamics of this industry. Moreover, it would be possible to extend these findings to other non-renewable natural resources markets.

APPENDIX A

Appendix to Chapter 3

A.1 Variable and Marginal Costs

Given the production function:

$$q_{it} = (\ell_{it})^{\alpha_\ell} \quad (e_{it})^{\alpha_e} \quad (f_{it})^{\alpha_f} \quad (k_{it})^{\alpha_k} \quad (r_{it})^{\alpha_r} \quad (g_{it})^{\alpha_g} \quad \exp\{\omega_{it}\} \tag{A.1.1}$$

and the definition of variable cost:

$$VC_{it} \equiv p^{\ell}_{it}\ell_{it} + p^{e}_{it}e_{it} + p^{f}_{it}f_{it} \tag{A.1.2}$$

we can derive the variable cost function as the solution to:

$$\begin{aligned}\mathcal{L} &= p_{it}^{\ell}\ell_{it} + p_{it}^{e}e_{it} + p_{it}^{f}f_{it} \\ &+\lambda\left[q_{it} - (\ell_{it})^{\alpha_\ell}(e_{it})^{\alpha_e}(f_{it})^{\alpha_f}(k_{it})^{\alpha_k}(r_{it})^{\alpha_r}(g_{it})^{\alpha_g}\exp\{\omega_{it}\}\right]\end{aligned} \tag{A.1.3}$$

the first order conditions for each variable input are:

$$\ell_{it} = \left[\left(\frac{q_{it}}{(k_{it})^{\alpha_k}(r_{it})^{\alpha_r}(g_{it})^{\alpha_g}\exp\{\omega_{it}\}}\right)\left(\frac{p_{it}^{e}}{p_{it}^{\ell}}\frac{\alpha_\ell}{\alpha_e}\right)^{\alpha_e}\left(\frac{p_{it}^{f}}{p_{it}^{\ell}}\frac{\alpha_\ell}{\alpha_f}\right)^{\alpha_f}\right]^{\frac{1}{\alpha_v}} \tag{A.1.4}$$

$$e_{it} = \left[\left(\frac{q_{it}}{(k_{it})^{\alpha_k}(r_{it})^{\alpha_r}(g_{it})^{\alpha_g}\exp\{\omega_{it}\}}\right)\left(\frac{p_{it}^{\ell}}{p_{it}^{e}}\frac{\alpha_e}{\alpha_\ell}\right)^{\alpha_\ell}\left(\frac{p_{it}^{f}}{p_{it}^{e}}\frac{\alpha_e}{\alpha_f}\right)^{\alpha_f}\right]^{\frac{1}{\alpha_v}} \tag{A.1.5}$$

and,

$$f_{it} = \left[\left(\frac{q_{it}}{(k_{it})^{\alpha_k}(r_{it})^{\alpha_r}(g_{it})^{\alpha_g}\exp\{\omega_{it}\}}\right)\left(\frac{p_{it}^{\ell}}{p_{it}^{e}}\frac{\alpha_f}{\alpha_\ell}\right)^{\alpha_\ell}\left(\frac{p_{it}^{e}}{p_{it}^{f}}\frac{\alpha_f}{\alpha_e}\right)^{\alpha_e}\right]^{\frac{1}{\alpha_v}} \tag{A.1.6}$$

where $\alpha_v = \alpha_\ell + \alpha_e + \alpha_f$. Solving equations (A.1.4), (A.1.5) and (A.1.6) into equation (A.1.2) and rearranging terms, we get the variable cost as:

$$VC_{it} = \alpha_v\left[\frac{\left(p_{it}^{\ell}/\alpha_\ell\right)^{\alpha_\ell}\ \left(p_{it}^{e}/\alpha_e\right)^{\alpha_e}\ \left(p_{it}^{f}/\alpha_f\right)^{\alpha_f}}{(k_{it})^{\alpha_k}\ (r_{it})^{\alpha_r}\ (g_{it})^{\alpha_g}\ \exp\{\omega_{it}\}}\ q_{it}\right]^{(1/\alpha_v)} \tag{A.1.7}$$

Finally, taking derivatives with respect to q_{it}, we get the marginal cost as:

$$MC_{it} = \left(\frac{1}{\alpha_v}\right)\left(\frac{VC_{it}}{q_{it}}\right) \tag{A.1.8}$$

A.2 Euler Equation for Output

Let us consider the following Bellman equation:

$$V(r_t, g_t) = \max_{q_t} \left[R_t(q_t) - VC(q_t, r_t, g_t) + \beta\, \mathbb{E}_t \left(V(r_{t+1}, g_{t+1}) \right) \right] \tag{A.2.1}$$

with the variable cost function:

$$VC_t = \alpha_v \left[\frac{\left(p_t^{\ell}/\alpha_{\ell}\right)^{\alpha_{\ell}} \ (p_t^e/\alpha_e)^{\alpha_e} \ \left(p_t^f/\alpha_f\right)^{\alpha_f}}{(k_t)^{\alpha_k}\ (r_t)^{\alpha_r}\ (g_t)^{\alpha_g}\ \exp\{\omega_t\}}\ q_{it} \right]^{(1/\alpha_v)}$$

and transition functions for reserves and ore grades:

$$r_{t+1} = r_t - \frac{q_t}{g_t} + z_{t+1}^{(r)} \tag{A.2.2}$$

$$g_{t+1} = \frac{g_t\ \exp\{\delta_z^{(g)} z_t^{(r)} + \varepsilon_{t+1}^{(g)}\}}{(1+q_t)^{\delta_q^{(g)}}} \tag{A.2.3}$$

The first order condition is:

$$\frac{\partial V_t}{\partial q_t} = MR_t - MC_t + \beta\, \mathbb{E}_t \left(\frac{\partial V_{t+1}}{\partial r_{t+1}}\ \frac{\partial r_{t+1}}{\partial q_t} + \frac{\partial V_{t+1}}{\partial g_{t+1}}\ \frac{\partial g_{t+1}}{\partial q_t} \right) = 0 \tag{A.2.4}$$

Taking into account that $\frac{\partial r_{t+1}}{\partial q_t} = \frac{-1}{g_t}$ and $\frac{\partial g_{t+1}}{\partial q_t} = -\delta_q^{(g)} \frac{g_{t+1}}{(1+q_t)}$, we have that:

$$MR_t - MC_t - \beta\, \mathbb{E}_t \left(\frac{\partial V_{t+1}}{\partial r_{t+1}}\ \frac{1}{g_t} + \frac{\partial V_{t+1}}{\partial g_{t+1}}\ \delta_q^{(g)} \frac{g_{t+1}}{(1+q_t)} \right) = 0 \tag{A.2.5}$$

Taking envelope conditions with respect to reserves and ore grades:

[i] Envelope condition w.r.t. r_t:

$$\frac{\partial V_t}{\partial r_t} = -\frac{\partial VC_t}{\partial r_t} + \beta\, \mathbb{E}_t \left(\frac{\partial V_{t+1}}{\partial r_{t+1}} \right)$$

and taking into account that $\dfrac{\partial VC_t}{\partial r_t} = -\dfrac{\alpha_r}{\alpha_v}\dfrac{VC_t}{r_t} = -\alpha_r \dfrac{q_t}{r_t}\, MC_t$, we have:

$$\frac{\partial V_t}{\partial r_t} = \alpha_r \frac{q_t}{r_t} MC_t + \beta\, \mathbb{E}_t \left(\frac{\partial V_{t+1}}{\partial r_{t+1}} \right)$$

[ii] Envelope condition w.r.t. g_t:

$$\frac{\partial V_t}{\partial g_t} = -\frac{\partial VC_t}{\partial g_t} + \beta\, \mathbb{E}_t \left(\frac{\partial V_{t+1}}{\partial g_{t+1}} \, \frac{g_{t+1}}{g_t} \right)$$

and taking into account that $\dfrac{\partial VC_t}{\partial g_t} = -\dfrac{\alpha_g}{\alpha_v}\dfrac{VC_t}{g_t} = -\alpha_g \dfrac{q_t}{g_t}\, MC_t$, we have:

$$\frac{\partial V_t}{\partial g_t} = \alpha_g \frac{q_t}{g_t} MC_t + \beta\, \mathbb{E}_t \left(\frac{\partial V_{t+1}}{\partial g_{t+1}} \, \frac{g_{t+1}}{g_t} \right)$$

Given that we have two endogenous state variables, g_t and r_t, and only one decision variable, q_t. it is not possible to derive an standard Euler equation. However, given that our estimates of α_r in the production function is not significantly different from zero and also given that $\dfrac{q_t}{r_t}$ is a very small number for all the mines in our data, it is possible to argue that $\alpha_r \dfrac{q_t}{r_t} MC_t$ is very close to zero, and therefore $\dfrac{\partial V_t}{\partial r_t}$ should be also very close to zero. In contrast, our estimate of α_g in the production function is large and $\dfrac{q_t}{g_t}$ is also a large number for the mines in the sample, then $\alpha_g \dfrac{q_t}{g_t} MC_t$ should be large, therefore, the depletion effect through ore grade is potentially quite important. Under this assumption, we can re-write the first order condition (A.2.4) as:

$$\frac{\partial V_t}{\partial q_t} = MR_t - MC_t + \beta\, \mathbb{E}_t \left(\frac{\partial V_{t+1}}{\partial g_{t+1}} \, \frac{\partial g_{t+1}}{\partial q_t} \right) = 0 \tag{A.2.6}$$

From transition rule of ore grades, we have that:

$$\begin{aligned} \frac{\partial g_{t+1}}{\partial q_t} &= \left(-\delta_q^{(g)}\right) (1+q_t)^{-\left(\delta_q^{(g)}+1\right)} g_t \exp\{\delta_z^{(g)} z_t^{(r)} + \varepsilon_{t+1}^{(g)}\} \\ &= \left(-\delta_q^{(g)}\right) \frac{g_{t+1}}{(1+q_t)} \end{aligned} \tag{A.2.7}$$

Solving into equation (A.2.6):

$$MR_t - MC_t - \beta\,\mathbb{E}_t\left(\frac{\partial V_{t+1}}{\partial g_{t+1}}\;\delta_q^{(g)}\frac{g_{t+1}}{(1+q_t)}\right) = 0 \tag{A.2.8}$$

The envelope condition with respect to g_t is:

$$\frac{\partial V_t}{\partial g_t} = \alpha_g \frac{q_t}{g_t} MC_t + \beta\,\mathbb{E}_t\left(\frac{\partial V_{t+1}}{\partial g_{t+1}}\;\frac{g_{t+1}}{g_t}\right) \tag{A.2.9}$$

Equation (A.2.6) implies that:

$$\beta\,\mathbb{E}_t\left(\frac{\partial V_{t+1}}{\partial g_{t+1}}\;\delta_q^{(g)}\frac{g_{t+1}}{(1+q_t)}\right) = MR_t - MC_t$$

Or:

$$\beta\,\mathbb{E}_t\left(\frac{\partial V_{t+1}}{\partial g_{t+1}}\;\frac{g_{t+1}}{g_t}\right) = \frac{MR_t - MC_t}{\delta_q^{(g)}}\;\frac{(1+q_t)}{g_t} \tag{A.2.10}$$

Solving equation (A.2.10) into equation (A.2.9) and given that $\frac{\partial g_{t+1}}{\partial g_t} = \frac{g_{t+1}}{g_t}$, we have:

$$\frac{\partial V_t}{\partial g_t} = \alpha_g \frac{q_t}{g_t} MC_t + \left(\frac{MR_t - MC_t}{\delta_q^{(g)}}\;\frac{(1+q_t)}{g_t}\right) \tag{A.2.11}$$

This implies that at $t+1$, we have:

$$\begin{aligned}
\left(\frac{\partial V_{t+1}}{\partial g_{t+1}}\;\delta_q^{(g)}\frac{g_{t+1}}{(1+q_t)}\right) &= \alpha_g \frac{q_{t+1}}{g_{t+1}} MC_{t+1}\;\delta_q^{(g)}\frac{g_{t+1}}{(1+q_t)} \\
&\quad + \left(\frac{MR_{t+1} - MC_{t+1}}{\delta_q^{(g)}}\;\frac{(1+q_{t+1})}{g_{t+1}}\right)\;\delta_q^{(g)}\frac{g_{t+1}}{(1+q_t)} \\
&= \alpha_g \delta_q^{(g)}\frac{q_{t+1}}{(1+q_t)} MC_{t+1} + \left([MR_{t+1} - MC_{t+1}]\;\frac{(1+q_{t+1})}{(1+q_t)}\right)
\end{aligned}$$

Therefore, the Euler equation is:

$$MR_t - MC_t = \beta\,\mathbb{E}_t\left([MR_{t+1} - MC_{t+1}]\;\frac{(1+q_{t+1})}{(1+q_t)} + \alpha_g \delta_q^{(g)}\frac{q_{t+1}}{(1+q_t)} MC_{t+1}\right)$$

A.3 Euler Equation for Discrete Choice Active/Non Active

Let us consider a simplified version of the binary entry/exit decision problem:

$$\begin{aligned} V^P(X_t) &= \max_{P(X_t)\in[0,1]} \Big\{ \pi^e_t(X_t, P_t) \\ &\quad + \beta \sum_{Z_{t+1}} f_z(Z_{t+1}|Z_t)[P_t(0|X_t)\pi^e_{t+1}(0, Z_{t+1}, P_{t+1}) + P_t(1|X_t)\pi^e_{t+1}(1, Z_{t+1}, P_{t+1})] \Big\} \end{aligned}$$

subject to

$$f^e_{t\to t+2}(1|X_t, P_t, P_{t+1}) = \sum_{Z_{t+1}} f_Z(Z_{t+1}|Z_t)[P_t(0|X_t)P_{t+1}(1|0, Z_{t+1}) + P_t(1|X_t)P_{t+1}(1|1, Z_{t+1})]$$

Therefore, the free probabilities that enter in the Lagrangian problem are $P_t(1|X_t)$, $P_{t+1}(1|0, Z_{t+1})$ and $P_{t+1}(1|1, Z_{t+1})$.

$$\begin{aligned} \mathcal{L} &= \pi^e_t(X_t, P_t) \\ &\quad + \beta \sum_{Z_{t+1}} f_z(Z_{t+1}|Z_t)[P_t(0|X_t)\pi^e_{t+1}(0, Z_{t+1}, P_{t+1}) + P_t(1|X_t)\pi^e_{t+1}(1, Z_{t+1}, P_{t+1})] \\ &\quad - \lambda(X_t) \sum_{Z_{t+1}} f_z(Z_{t+1}|Z_t)[P_t(0|X_t)P_{t+1}(1|0, Z_{t+1}) + P_t(1|X_t)P_{t+1}(1|1, Z_{t+1})] \end{aligned} \tag{A.3.1}$$

The marginal condition with respect to one of the probabilities $P_{t+1}(1|X_{t+1})$ is $\beta \frac{\partial \pi^e_{t+1}(1, Z_{t+1}, P_{t+1})}{\partial P_{t+1}(1|1, Z_{t+1})} = \beta \frac{\partial \pi^e_{t+1}(0, Z_{t+1}, P_{t+1})}{\partial P_{t+1}(1|0, Z_{t+1})} = \lambda(X_t)$. Substituting the marginal condition with respect to $P_{t+1}(1|X_{t+1})$ into the marginal condition with respect to $P_t(1|X_t)$, we get the Euler equation:

$$\frac{\partial \pi_t^e(X_t, P_t)}{\partial P_t(1|X_t)} + \beta E_t\left[\pi_{t+1}^e(1, Z_{t+1}) - \pi_{t+1}^e(0, Z_{t+1})\right]$$
$$+\beta E_t\left[P_{t+1}(1|0, Z_{t+1})\frac{\partial \pi_{t+1}^e(0, Z_{t+1})}{\partial P_{t+1}(1|0, Z_{t+1})} - P_{t+1}(1|1, Z_{t+1})\frac{\partial \pi_{t+1}^e(1, Z_{t+1})}{\partial P_{t+1}(1|1, Z_{t+1})}\right] = 0 \tag{A.3.2}$$

Assuming a logit specification for the unobservables, we have that the marginal expected profits are:

i) $\frac{\partial \pi_t^e}{\partial P_t(1|X_t)} = \pi_t(1, y_t, Z_t) - \pi_t(0, y_t, Z_t) - \sigma_\varepsilon \ln\left(\frac{P_t(1|y_t, Z_t)}{P_t(0|y_t, Z_t)}\right)$

ii) $\frac{\partial \pi_{t+1}^e}{\partial P_{t+1}(1|0, Z_{t+1})} = \pi_{t+1}(1, 0, Z_{t+1}) - \pi_{t+1}(0, 0, Z_{t+1}) - \sigma_\varepsilon \ln\left(\frac{P_{t+1}(1|0, Z_{t+1})}{P_{t+1}(0|0, Z_{t+1})}\right)$

iii) $\frac{\partial \pi_{t+1}^e}{\partial P_{t+1}(1|1, Z_{t+1})} = \pi_{t+1}(1, 1, Z_{t+1}) - \pi_{t+1}(0, 1, Z_{t+1}) - \sigma_\varepsilon \ln\left(\frac{P_{t+1}(1|1, Z_{t+1})}{P_{t+1}(0|1, Z_{t+1})}\right)$

Moreover, we know that:

iv) $\pi_{t+1}^e(1, Z_{t+1}) = P_{t+1}(0|1, Z_{t+1})[\pi_{t+1}(0, 1, Z_{t+1}) - \sigma_\varepsilon \ln P_{t+1}(0|1, Z_{t+1})]$
$+ P_{t+1}(1|1, Z_{t+1})[\pi_{t+1}(1, 1, Z_{t+1}) - \sigma_\varepsilon \ln P_{t+1}(1|1, Z_{t+1})]$

v) $\pi_{t+1}^e(0, Z_{t+1}) = P_{t+1}(0|0, Z_{t+1})[\pi_{t+1}(0, 0, Z_{t+1}) - \sigma_\varepsilon \ln P_{t+1}(0|0, Z_{t+1})]$
$+ P_{t+1}(1|0, Z_{t+1})[\pi_{t+1}(1, 0, Z_{t+1}) - \sigma_\varepsilon \ln P_{t+1}(1|0, Z_{t+1})]$

Solving equations $i)$ to $v)$ into equation A.3.2 and operating in the probabilities, we get the Euler equation:

$$\left[\pi_t(1, y_t, Z_t) - \pi_t(0, y_t, Z_t) - \sigma_\varepsilon \ln\left(\frac{P_t(1|y_t, Z_t)}{P_t(0|y_t, Z_t)}\right)\right]$$
$$+\beta E_t\left[\pi_{t+1}(1, 1, Z_{t+1}) - \pi_{t+1}(1, 0, Z_{t+1}) - \sigma_\varepsilon \ln\left(\frac{P_{t+1}(1|1, Z_{t+1})}{P_{t+1}(1|0, Z_{t+1})}\right)\right] = 0$$

APPENDIX B

Appendix to Chapter 7

B.1 Derivation of the Conduct Parameter

Assuming that firms choose to produce a quantity q_i which maximizes its profit Π_i, then the firm $i's$ profit maximization problem can be written as:

$$\underset{q_{it}}{\text{Max}}\, \Pi_{it} = P\left(Q_t, X_t, \alpha\right) q_{it} - C\left(q_{it}, W_{it}, \beta\right)$$

The first order condition is given by:

$$\begin{aligned} \frac{\partial \Pi_{it}}{\partial q_{it}} &= P_t + q_{it} \frac{\partial P\left(Q_t, X_t, \alpha\right)}{\partial Q} \frac{\partial Q}{\partial q_i} - MC_i\left(q_{it}, W_t, \beta_i\right) = 0 \\ P_t &= MC_i\left(q_{it}, W_t, \beta_i\right) - q_{it} \frac{\partial P\left(Q_t, X_t, \alpha\right)}{\partial Q} \frac{\partial Q}{\partial q_i} \end{aligned}$$

Multiplying both sides by $\frac{Q}{P}$:

$$P_t = MC_i(q_{it}, W_t, \beta_i) - \frac{\partial P(Q_t, X_t, \alpha)}{\partial Q}\frac{Q}{P}\frac{\partial Q}{\partial q_i}\frac{q_{it}}{Q}P_t$$

given that $\eta_t = -\frac{\partial Q}{\partial P}\frac{P_t}{Q_t}$ is the price elasticity of demand, this equation can be re-written as:

$$P_t = MC_i(q_{it}, W_t, \beta_i) + \frac{P_t}{\eta_t}\frac{\partial Q}{\partial q_i}\frac{q_{it}}{Q}$$

Summing over firms, this supply relationship can be written on an industry level as:

$$P_t = \sum_{i=1}^{n} s_{it}MC_{it} + \frac{P_t}{\eta_t}\sum_{i=1}^{n} s_{it}\frac{\partial Q}{\partial q_i}\frac{q_{it}}{Q}$$

The Term $\sum_{i=1}^{n} s_{it}\frac{\partial Q}{\partial q_i}\frac{q_{it}}{Q}$ represents the response of total market to firm $i's$ change in production. Now, it is possible to write a conduct parameter, θ_t, nesting several market structures as:

$$\theta_t = \sum_{i=1}^{n} s_{it}\frac{\partial Q}{\partial q_i}\frac{q_{it}}{Q}$$

In a static perfect competition equilibrium, the firms are too small compared to the total market. Therefore $\frac{\partial Q}{\partial q_i}\frac{q_{it}}{Q} = 0$. The best response for a firm in a static Cournot game is to produce up to its capacity, then an increase of one percent in firm $i's$ quantity will lead to an increase of one percent in the total market quantity. Therefore, $\frac{\partial Q}{\partial q_i}\frac{q_{it}}{Q} = s_{it}$ and $\theta_t = s_{it}^2$, which is the Herfindahl Index, if firms are symmetric, then $\theta_t = \frac{1}{n}$. In a static monopoly, if the firm i increase its quantity in an x percent, all other firms will increase their quantity in the same x percent, then $\frac{\partial Q}{\partial q_i}\frac{q_{it}}{Q} = 1$. Therefore, the supply relationship can be re-written on an industry level as:

$$P_t = MC(Q_t, W_t, \beta_i) + \theta_t\frac{P_t}{\eta_t},$$

B.2 Monopoly and Cournot Pricing Rules

Consider the following general form of the demand curve:

$$Q(P) = \beta\,(\alpha - P)^{\gamma}$$

where Q is the quantity demanded of copper and P is the price of copper. This specification includes several cases for the demand function: $\gamma = 1$ for the linear demand function, $\gamma = 2$ for the quadratic demand function, and $\alpha = 0$ $\gamma = 1$ for the log-linear demand function. For simplicity, we choose to use the linear demand function. The corresponding demand equation is as follow:

$$Q = \beta\,(\alpha - P) + \epsilon$$

To correct for potential endogeneity problems, we use wage and energy as instruments for price (See table 7.1).

The implied monopoly price under constant marginal cost c, $P^M\,(c)$ satisfies

$$P^M\,(c) = \frac{\alpha + \gamma c}{1 + \gamma}$$

Finally, the implied n-firm symmetric Cournot price under constant marginal cost c, $P^N(c)$ satisfies:

$$P^N(c) = \frac{\frac{1}{n}\alpha + \gamma c}{1 + \gamma \frac{1}{n}}$$

Therefore, the implied monopoly and Cournot pricing rule are $285.42 + 0.5c$ and $51.89 + 0.91c$, respectively. Using the mean of the direct cash costs (90.04 cents per pound) as proxy for the mean of marginal cost, the implied price are 330.43 and 133.72 cents per pound of copper, respectively.

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